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Control strategies for power distribution networks with electric vehicles integration

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Kongens Lyngby, January 2014
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Control strategies for power distribution networks with electric vehicles integration

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Summary

Demand side resources, like electric vehicles (EVs), can become integral parts of a smart grids because instead of just consuming power they are capable of providing valuable services to power systems. EVs can be used to balance the intermittent renewable energy resources such as wind and solar. EVs can absorb energy during periods of high electricity production and feed the electricity back into the grid when the demand is high or in situations of insufficient electricity generation. However, extra loads created by the increasing number of EVs may have adverse impacts on the distribution network such as congestion. These factors will bring new challenges to the distribution system operator. Typically, the challenges are solved by expanding the grid to fit the size and the pattern of the demand. As an alternative, the capacity problem can also be solved smartly using advanced control strategies supported by an increased use of information and communication technology. This is the idea of the smart grid. The smart grid is a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery and consumption of electrical energy. A smart grid can also be defined as an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both - in order to efficiently deliver sustainable, economic and secure electricity supplies.

This thesis focuses on designing control strategies for congestion control in distribution network with multiple actors, such as the distribution system operator (DSO), fleet operators (FO), and electric vehicle owners (or prosumers), considering their self-interests and operational constraints. Note that the control problem investigated here deals with “higher level” control, e.g., optimization strategy algorithms related scheduling instead of “lower level” direct process control. The thesis starts with reviewing innovative control strategies for large scale management of EVs in the power systems including centralized direct control, market based control, and price control. The thesis investigates new approaches for distribution networks congestion management. It suggests and develops a market based control for distribution grid congestion management. The general equilibrium market mechanism is utilized in the operation of the

market.

To build a complete solution for integration of EVs into the distribution network, a price coordinated hierarchical scheduling system is proposed which can well characterize the involved actors in the smart grid. With this system, we demonstrate that it is possible to schedule the charging scheme of EVs according to the users' energy driving requirements and the forecasted day-ahead electricity market price. Several electric vehicle fleet operators are specified to manage the electric vehicle fleets. The method of market based control can then be used by the DSO to interact with the electric vehicle fleet operators to eliminate the grid congestion problem. Note that the electric vehicle fleet operator can manage the EVs based on the three aforementioned control strategies. To test and evaluate the proposed control strategies, multi-agent concepts is used to model the price coordinated hierarchical scheduling system. To implement and demonstrate the multi-agent systems, a novel simulation platform has been developed based on the integration of JACK (a Java based agent-oriented development environment) and Matlab/Simulink software.

Resumé

Elektrisk drevne køretøjer kan udover at forbruge energi også bidrage aktivt til elforsyningen ved balancering af grønne intermitterende energikilder såsom vindmøller og solceller. Elektriske køretøjer kan således absorbere energi i perioder med overproduktion og levere energien tilbage til el nettet i situationer med forøget efterspørgsel eller utilstrækkelig produktion. Et øget antal elektriske køretøjer vil imidlertid også have negativ indflydelse på elforsyningen, idet de i nogle situationer kan forårsage overbelastning af forsyningslinjer eller andet udstyr i nettet. Eldistributionselskaberne vil derfor få nye udfordringer når antal af elektriske køretøjer forøges. Udvidelser af nettet med flere forsyningslinjer til håndtering af den øgede belastning er en af de mulige løsninger. Overbelastning af nettet kan imidlertid også imødegås ved en øget anvendelse af informations og kommunikationsteknologi (IKT) til intelligent styring. Dette er ideen bag udviklingen af “smart-grid”, som er fremtidens elforsynings system karakteriseret ved en øget anvendelse af IKT i hele forsyningskæden fra produktion, leverance og forbrug af elektrisk energi.

Afhandlingen emne er udvikling af styringsstrategier for håndtering af overbelastning i eldistributions net med mange aktører såsom netoperatører, flådeoperatører samt ejere af elektriske køretøjer. Styrings-strategierne udformes således at de tager hensyn til aktørernes interesser samt nettets driftsbegrænsninger. Afhandlingen fokuserer på overordnede strategier til optimering af driftsplaner (schedules) for nettet og de forbundne køretøjer. Styring af de enkelte køretøjer er således ikke behandlet.

Afhandlingen indledes med en oversigt over innovative strategier for overordnet håndtering af elektriske køretøjer i elforsyningen omfattende centraliseret direkte styring samt markeds- og prisbaseret styring. Derefter udvikles en strategi for markeds-baseret styring af distributionsnettet som håndterer overbelastninger (congestion) baseret på “general equilibrium market” mekanismer. Derudover foreslås en prisbaseret hierarkisk styring til integration af elektriske køretøjer i distributionsnettets drift, som muliggør inddragelse af aktørernes interesser. Det demonstreres at når disse to styringsprincipper kombineres er det muligt at schedulere opladningen af elektriske køretøjer under hensyntagen til

brugernes behov for energi til transport samt dagsprisen for elektricitet på day-ahead markedet. Det udviklede styringsprincip understøtter mere end en fleet operatør og markedsbaseringen gør det muligt for netoperatøren at interagere med dem ved håndteringen af overbelastningssituationer i eldistributionsnettet. Flådeoperatører kan tillige anvende centraliseret direkte styring, markedsbaseret eller prisbaseret styring af de enkelte elektriske køretøjer. De udviklede strategier demonstreres og evalueres ved en implementering baseret på en integration af multiagent software teknologi (JACK) samt Matlab/Simulink software.

Preface

This thesis was prepared at Center for Electric Power and Energy, Department of Electrical Engineering, Technical University of Denmark in partial fulfillment of the requirements for acquiring the Ph.D. degree in engineering.

This thesis deals with developing control strategies for large scale integration of EVs into the power distribution network. It mainly addresses applications of market based control strategy for cost efficient and flexible control of distributed electric vehicles within the distribution networks. The research questions are derived from the state of the art in the electric power systems and the new challenges and requirements faced by the power industry. The project has been mainly supported by and connected to two Danish research and innovation projects, the Edison project ¹ and the iPower project ². In the beginning of the PhD study, I was mainly working on the subject of electric vehicle smart charging, learning from the discussions and results generated from the Edison project (the project was finished around the middle of 2011). Then, gradually, my working time and attention were moving to the subject which is investigated in the iPower project (mainly work package 3, 4), i.e., distribution grid congestion related research. An outcome of this work package is the FLECH (flexibility clearing house) platform. In addition, the PhD student would like to thanks the support from the Ph.D. Programs Foundation of Ministry of Education of China under the grant (20100072110038).

In general, the research topics of the PhD project are inspired by the discussion from the Edison and iPower project, but the method developments such as market based control for distribution grid congestion management are almost independent from the iPower project. Furthermore, we took the decision to model and evaluate the market based control approach developed for solving distribution grid congestion in a multi-agent system. Currently, our multi-agent systems based platform has been proposed and preliminarily used to support the FLECH mock up platform simulation which is more flexible and can simulate various services required by the distribution system operator.

¹<http://www.edison-net.dk/>

²<http://www.ipower-net.dk/>

This thesis consists of a summary report and a collection of nine research papers written during the period 2011–2013.

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Firstly, I would like to express my sincere gratitude to my supervisor Professor Emeritus Morten Lind for his kind supervision, patience and mentoring during the course of my PhD study. He has always been a source of guidance and inspiration during the research and writing of this thesis as well as on philosophy of science, engineering and life in general. I would also like to express my heartfelt gratitude to my supervisor Prof. Jacob Østergaard for his motivation, instructive supervision and guidance during the course of my PhD study. He has been an example of pursuing excellence during my study and will always be an example for my future career.

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Glossary

Battery pack

A battery pack is the final assembly used to store and discharge electric energy in a EV.

Battery State of charge (SOC)

The available capacity in a battery expressed as a percentage of rated nominal capacity.

Centralized direct control

The up-level controller directly schedule and specify the low-level units to execute the commands. It can be applied to both the control relations between the DSO and the fleet operators in term of grid capacity allocations and between the fleet operators and the individual electric vehicles in term of charging operation.

Demand side resources (DSR)

DSR refers to the geographically distributed modular power generation, consumption and energy storage systems which are located on the demand side and have the capability of altering their consumption pattern.

Distributed energy resources (DER)

A power producing or consuming unit connected to a distribution system with communication and explicit control capabilities that could be employed to support the electricity grid.

Distribution system operator (DSO)

A system operator responsible for distribution systems.

Electric vehicle (EV)

EV is defined as passenger vehicle exclusively with an electric drive.

Electric vehicle fleet operator (EV FO)

EV FO is used to manage electric vehicle and represent them to interact with the market. EV FO could be independent or integrated in an existing business function of the energy supplier. Simply, in this thesis, FO means EV FO.

Flexibility clearing house (FLECH)

A platform developed in the Danish iPower project (<http://www.ipower-net.dk/>) for facilitating ancillary services at the distribution system level.

Market based control

Market based control is a paradigm for controlling complex systems with conflicting resources. It typically includes the features found in a market such as decentralized decision making and interacting agents. Market based control usually requires two way communication, e.g., exchange the price and power schedule information. It can be applied to both the control relations between the DSO and the fleet operators in term of grid capacity allocations and between the fleet operators and the individual electric vehicles in term of charging operation.

Price control

Price control applies broadcasting of price signal with a regular update frequency to the demand side resource. Price control is in the form of one way communication. It can be applied to both the control relations between the DSO and the fleet operators in term of grid capacity allocations and between the fleet operators and the individual electric vehicles in term of charging operation.

Transmission system operator (TSO)

A System Operator responsible for the transmission system.

Vehicle to grid (V2G)

V2G describes a system in which plug-in electric vehicles connect to the power grid to deliver the electricity into the grid.

Introduction

1.1 Background

An important means used by the power industry to reduce greenhouse gas emission and fossil fuel dependency is the introduction of renewable energy resources, such as wind and solar generation. Denmark was a pioneer in wind power which provides a large amount of electricity to consumers. By the end of 2012, the total installed wind capacity in the Danish power systems was 4162 MW counting 30.1% of the domestic electricity usage [1]. Wind energy in Denmark is expected to grow due to the political strategy of achieving 50% wind power in the 2020 Danish power system [2]. The most installed wind power in Denmark is connected at the distribution system level, which brings challenges to Energinet.dk (transmission system operator (TSO) of Denmark). Energinet.dk has limited or no access to the information about the status at the medium grid voltage level. In order to address the challenges, several actions [3] have been implemented or planned, such as:

- Coordination of the power flows among different systems by electrical interconnections, mostly high voltage direct current to the TSOs in the Sweden, Norway, Germany, and soon the Netherland.
- Balancing the power systems by the deregulated power market with the collaborations of power balance responsible parties. The balance responsible parties make the power and energy bids into the market, consisting of conventional power and wind power.
- Implementing tools to provide real time estimation of the amount of power injections from wind energy.

- Managing the flexible demand, like electric vehicles (EVs), heat pumps in the residential area, large industrial factory and commercial buildings etc.

In order to manage the flexible demand, such as electric vehicles' flexibilities, a research project in Denmark with international collaboration named Edison project ¹ was funded to develop optimal system solutions for electric vehicles system integration, including EV battery technology, networks issues, market solutions, information and communication technology standard development. To utilize the full benefit of the interaction between the electric vehicles and the power grid with a large amount of power from fluctuating sources, softwares that enables electric vehicles to charge when there is a surplus of energy in the system or to resupply energy to the grid when there is a lack of power in the system are developed. The major control concept in the Edison project is the introduction of a fleet operator (FO) to aggregate the consumption of a number of electric vehicles and handle their interaction with the electricity market as one unit with a centralized/direct control [4–6] to capture the full benefits. Insights from the project indicated that distribution grid congestion may happen with the utilization of smart charging scheme [7–9]. In order to solve the grid congestion caused by the newly increasing demand, well defined control strategies are required for the power distribution systems and this is the main research topic of this PhD project.

1.2 Objectives and research problems

1.2.1 Overall objectives

This thesis deals with development of control strategies for large scale integration of electric vehicles into the power distribution network. Fig. 1.1 illustrates the relevant actors, operations, and the available control strategies in the considered systems. We hypothesize that it is possible to schedule the charging scheme of electric vehicles according to the users' energy driving requirements and the forecasted day ahead electricity market price. Several fleet operators are specified to manage the EV fleets, then distribution system operator (DSO) can interact with the fleet operators to eliminate the grid congestions. Note that the dispatch currently used is defined only based on the spot market and the regulation market. The state of the distribution grid is not considered. We aim to develop a control strategy for distribution grid congestion management before the resource dispatch. Our objectives are to coordinate the self interests

¹<http://www.edison-net.dk/>

and operation constraints of three types of actors in the market: the EV owner, the fleet operators and the distribution system operator facilitated by the developed control strategies, e.g., considering the individual EV owner's driving requirement, the charging cost of electric vehicle, the fleet operator's business objectives and the thermal limits of cables and transformers of distribution grid.

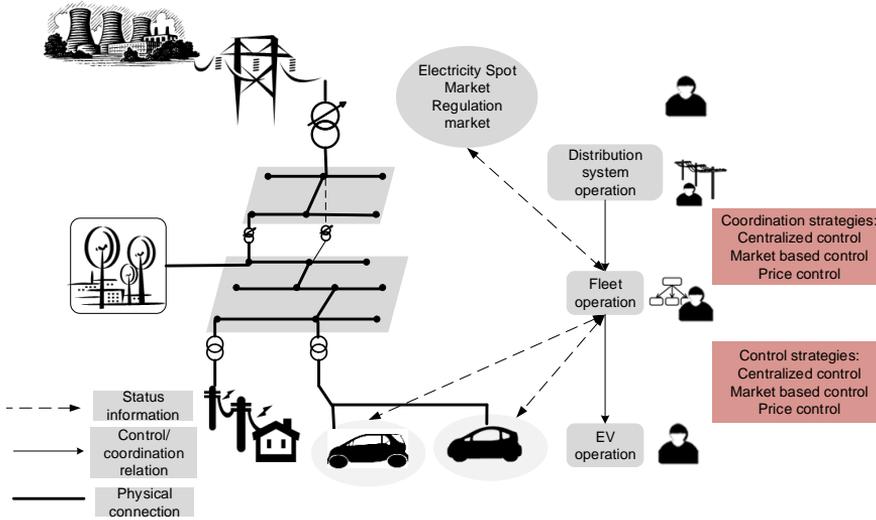


Figure 1.1: Power system with electric vehicles integration coordinated by fleet operators

1.2.2 Problems analysis

In the deregulated electric power industry, the system described in Fig. 1.1 can be regarded as a typical decentralized, hierarchically organized system. The substantial characteristic of such system is their decomposability into a series of individual functional levels [10]. The functional levels of the system usually include: Level 4, plant management, Level 3, production scheduling, Level 2, plant supervisory control, and Level 1, direct process control. At each level, some automation functions are implemented to operate on the next "lower" level. The execution of function is, however, initiated and controlled by the next "higher level". With this four-stage system, the structural and functional properties of a hierarchical system can be explained. The control problem investigated in this thesis is mainly referred to Level 3 production scheduling.

This level is responsible for a series of functions, belonging more to the area of operations research and resource allocation than to the systems or control engineering. Production scheduling/dispatching for the system according to the status of consumer's requirements, network constraints, and energy demands is the main concern of this level. At this level, the current existing control methods which are proposed to integrate large scale of distributed energy resources into the power systems including centralized control, market based and price control ². Fig. 1.2 overviews the control methods. Note that the local control method is considered, although it is effective and simple to be implemented. In addition to this, the local control can be put inside the price control category, for example, the units can set up a command that the device will be turned on if the price is lower than a threshold value.

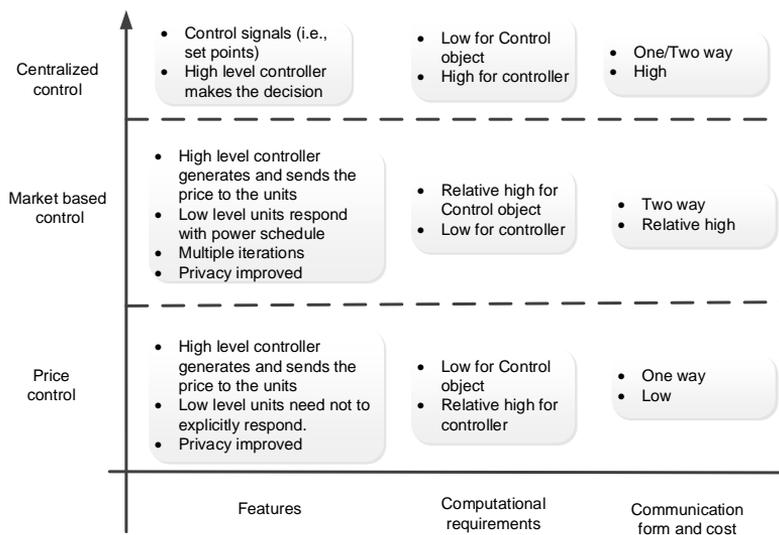


Figure 1.2: Control strategies overview

Given the three control strategies, the overall problems of developing control strategies for large scale integration of electric vehicles into the power distribution network have been decomposed into three subproblems:

1. In order to manage a large scale of electric vehicles, from a commercial

²In addition to the centralized control adopted in the Edison project, market based control and price control are also proposed by other research, more details will be explained in next Chapter regarding state of the art.

actor (fleet operator) or system operator's ³ perspective, what are the implications, advantages and disadvantages when choosing a control strategy? Furthermore, how to design the control algorithms and what are the necessary information and communications that are required to support the chosen control strategy?

2. To address the congestion issue of distribution network, with a condition that we can benefit more by using the advocated three control strategies except the traditional way of upgrading the grid, what are the implications, advantages and disadvantages for the system operator, the commercial players, and the EV owners when choosing a control strategy? In addition, how to devise the control algorithms and what are the necessary information and communications that are required to support the chosen control strategy?
3. Development of tools to simulate the control strategies developed for distribution grids congestion management with electric vehicle integration considering variously involved actors and different domains.

These three subproblems has been turned into three research topics of this project which will be elaborated in below. The three research topics are:

1. Optimization and control for integrating electric vehicles.

The thesis starts to review and compare the control strategies for integrating the increasing number of electric vehicles into the power systems. Then, it investigates control algorithms which support the various control strategies such as linear programming, dynamic programming and mixed integer linear programming based techniques.

2. Market based control for distribution gird congestion management.

In this research topic, the market based control is used to prevent the grid congestion. The focus has been divided into two perspectives: one is to find the suitable price clearing algorithms for the actors inside the market taking into account the effectiveness, the computation cost, and the generality; another one is to find the suitable optimization techniques which support the actors' participation in the market. Note that the market based control out of the three control methods is chosen, mainly due to the following reasons: 1) It fits with the deregulated electricity market environment. 2) The congestion management in the transmission systems is managed according the market based control method. 3) The

³Note that the commercial actor might not exists if the business opportunity is not attractive. Under the circumstances, the DSO needs to control or coordinate the charging behaviors of EVs to avoid the grid congestion.

introduction of the FOs make it possible to manage the congestion in a market based approach. 4) The certainty of the problem solving is higher than the price control and the computation requirements for the system operator is lower than the centralized control.

3. Multi-agent system for distribution grid congestion management

The research focuses on develop modeling framework and tools for distribution grid congestion management study. Precisely, multi-agents system is used for modeling and evaluation of the developed control strategies for distribution grid congestion management. The aim is to prove that multi-agent system is a suitable technology to fulfill the requirements.

1.3 Research contributions

The main contributions of the research consist of:

- We present a comprehensive review of the optimization and control methods that are used in integrating electric vehicles into the power systems. It outlines the advantages and disadvantages of various control strategies, presents the details of the modeling method and algorithms in each control strategy. Details are presented in separate papers [A.1](#), [A.2](#), [A.3](#), and [A.4](#) and Chapter [3](#) gives a summary of the main results.
- A price coordinated hierarchical scheduling/control system has been developed and demonstrated successfully for the integration of the distributed energy resources into the power distribution networks. In the system, we apply a market based control strategy to solve the distribution grid congestion. The price clearing algorithm used in this market falls into the general equilibrium market scheme. We use the electric vehicles as case to illustrate the systematic integration of distributed energy resources into the distribution network. With the case, we also demonstrate that various control methods used by the fleet operator such as direct control, price control can be flexibly integrated into this hierarchical control systems. Details are presented in separate papers [A.5](#), [A.6](#), [A.7](#), and [A.8](#) and Chapter [4](#) gives a summary of the main results.
- A multi-agent technology has been motivated and used to simulate/demonstrate the proposed market scheme. We present a flexible and powerful simulation platform which is based on the integration of an agent based simulation tool JACK, computational tool Matlab, and grid simulation in

Simulink. The developed platform can support the simulation of intelligent control scheme for the smart grids. Details are presented in separate paper [A.9](#), [A.10](#) and Chapter 5 gives a summary of the main results.

1.4 Publications

We present these contributions by providing both a summary report as the main content of this thesis and a number of papers that we have written throughout the project period attached in the appendix. Totally 10 papers are included in appendices [A.1](#) through [A.10](#). The papers are referenced throughout this report as needed, but may also be read independently of this report. Papers [A.1](#) to [A.10](#) contain the main results of the project, and are included as appendices. Papers from [11](#) onwards contain other contributions from the author that are not directly related to the PhD thesis.

[A.1](#): J. Hu, S. You, C. Si, M. Lind, and J. Østergaard, *Optimization and control methods for smart charging of electric vehicles facilitated by fleet operator: review and classification*. International journal of distributed energy resources and smart grids, 2014.

[A.2](#): J. Hu, S. You, M. Lind, J. Østergaard, and Q. Wu, *Optimal charging schedule of an electric vehicle fleet*, in proceedings of 46th International Universities' power engineering conference (UPEC), 2011, Germany.

[A.3](#): T. Lan, J. Hu, Q. Kang, C. Si, L. Wang, Q. Wu, *Optimal control of an electric vehicle's charging schedule under electricity markets*, Neural computing and applications, 2012.

[A.4](#): S. You, J. Hu et al., *Numerical comparison of optimal charging schemes for electric vehicles*, in proceedings of IEEE PES general meeting, San Diego, U.S., 2012.

[A.5](#): P. B. Andersen, J. Hu, K. Heussen, *Coordination strategies for distribution grid congestion management in a multi-actor, multi-objective setting*, in proceedings of IEEE Innovative Smart Grid Technologies (ISGT) Berlin, 2012.

[A.6](#): J. Hu, S. You, M. Lind, and J. Østergaard, *Coordinated charging of electric vehicles for congestion prevention in the distribution grid*, To appear in IEEE transactions on smart grids, 2014.

[A.7](#): J. Hu, M. Lind, Saleem, A, S. You, and J. Østergaard, *Multilevel coor-*

dination in smart grids for congestion management of distribution grid, in proceedings of International conference on intelligent system applications to power systems (ISAP), 2013, Japan.

A.8: K. Heussen, D. E. Bondy, J. Hu, et al., *A clearinghouse concept for distribution-level flexibility services*, in proceedings of IEEE Innovative Smart Grid Technologies (ISGT) Copenhagen, 2013.

A.9: J. Hu, A. Saleem, S. You, L. Nordström, M. Lind, J. Østergaard, *A multi-agent system for distribution grid congestion management with electric vehicles*, Engineering Application of Artificial Intelligence, in submission, 2013.

A.10: J. Hu, H. Morais, M. Lind, J. Østergaard, *HV/MV power transformer capacity negotiation by fleet operators using multi-agents*, submitted to 12th International Conference on Practical Applications of Agents and Multi-Agent Systems, 2014.

11: J. Hu, M. Lind, S. You, X. Zhang, *Multilevel flow modeling of domestic heating systems*, proceedings of 2012 Symposium on Socially and Technically Symbiotic Systems (STSS), Japan.

12: W. Guo, D. Yang, J. Hu, C. Huang, L. Wang and Q. Wu, *Optimal management of a home smart grid scheduling*, Journal of Computational Information Systems, v 8, n 5, p 1921-1928, March 1, 2012.

13: S. You, J. Hu, et al., *Analytical framework for market-oriented DSR flexibility integration and management*, Energy and Power Engineering, ISSN Print: 1949-243X, 2012.

14: C. Si, T. Lan, J. Hu, L. Wang, Q. Wu, *On the penalty parameter of the penalty function method*, to appear in the journal Control and Decision, 2014. (In Chinese)

15: S. You, H. W. Bindner, J. Hu, *An Overview of trends in distribution network planning: A Movement Towards Smart Planning*, accepted for publication in IEEE PES, Transmission and distribution conference, 2014.

Table 1.1 summarizes contribution of the research paper to the three research topics of the PhD project.

In more details, for the first research topic, paper A.1 reviews the three control strategies for smart charging of electric vehicles. It outlines the information flows and presents the widely proposed control algorithms in the three different control strategies. The next three papers focus on methods development,

Research topics	Publication									
	A.1	A.2	A.3	A.4	A.5	A.6	A.7	A.8	A.9	A.10
1. Optimization and control for integrating electric vehicles	x	x	x	x						
2. Market based control for distribution grid congestion management.					x	x	x	x		
3. Multiagent system for distribution grid congestion management									x	x

Table 1.1: Relation between research topics and publications

i.e., using linear approximation and nonlinear approximation to characterize the battery charging issue and a formulation of the charging problem in a linear programming based charging cost minimization problem (paper [A.2](#)) and dynamic programming based charging cost minimization problem (paper [A.3](#)). Furthermore, vehicle to grid study is performed in paper [A.4](#) to perform the economic analysis considering its profits of providing regulation services and its battery degradation costs, mixed integer linear programming based formulation is used in this paper.

For the second research topic, paper [A.5](#) addresses the interactions between the stake-holders involved in the distribution system (the distribution system operator, the commercial actors, and the EV owners) when handling the distribution grid congestion problem, and identifies several approaches by which their diverse and potentially conflicting objectives can be coordinated. Paper [A.6](#) recommends and tests the market based control scheme identified in paper [A.5](#) with detailed mathematical explanation, proof and illustrations with case studies for congestion prevention. Paper [A.7](#) extends the study in paper [A.6](#) and proposes the price coordinated hierarchical control system to control the distribution grid congestion considering electric vehicle integration. Paper [A.8](#) introduces the flexibility clearinghouse (FLECH) concept and presents a case study of using electric vehicles to provide services to the distribution system operator.

For the third research topic, paper [A.9](#) extends the concepts in paper [A.6](#) and the extension mainly utilize the multi-agents system (MAS) technology to assess the proposed market scheme with the purpose of illustrating and tracking the coordination behaviors. Moreover, the extension considers demonstrating EVs' flexibility (through the presence of response weighting factor to the shadow price) in the developed MAS system. Paper [A.10](#) uses the multi-agents based

platform (developed in paper [A.9](#)) to simulate a collaborative but also competitive environment where multiple fleet operators negotiate on the transformer capacity of the distribution grid. In the study, each fleet operator do its EVs charging/discharging scheduling taking into account the network constraints.

1.5 Outline of the thesis

This thesis comprises 6 chapters. Chapter [1](#) introduces the overall problem and the research objectives of the project. Chapter [2](#) provides a review on the state of the art of the three sub-problems. In chapter [3](#), the electric vehicles integration research is presented in a compact way. In chapter [4](#), the developed market based control strategy is presented. Chapter [5](#) discusses the topic of multi-agent based modeling and simulation. Finally, in chapter [6](#), conclusions and future work are presented.

State of the art

In this chapter, existing literature and practices relevant to the three research problems of this PhD project are reviewed. First, in sec. 2.1, we review the potential business opportunities associated to electric vehicle fleet and the control strategies which are proposed to manage the electric vehicles. Second, in sec. 2.2, control strategies for solving the distribution grid congestion problem have been reviewed, especially, the review focuses on the methods which are proposed for the control relations between the distribution system operation and electric vehicle fleet operations. Finally, in sec. 2.3, the multiagent based system and their application in smart distribution grid operation and simulations are discussed. Note that as each paper attached in the appendices contains the literature studies and references relevant to the specific topic, the reference list in this chapter is not exhaustive, and the reader is referred to those given in the papers as well. Nevertheless, the aim is to include and present some studies with figures which facilitate further understanding.

2.1 Management of electric vehicle fleet and their business opportunities

Much research has been focused on electric vehicles integration into power system since the last decades. In this section, we review the publications based on its control objectives which are summarized from the existing studies, i.e., start with the discussion on how electric vehicles can be aggregated to provide ancillary service to transmission system operator; then present how electric vehicles can be used to maximize the production of renewable energy producers;

next, the discussion will be moved on to the proposed commercial actor, i.e., fleet operator; finally, the optimization methods of minimizing the charging cost of electric vehicles are examined.

Kempton et al. [11–14] analysed the potential profits of vehicle to grid (V2G) support by comparing it to existing ancillary services and found that participating regulation power market appears to be most promising and offers a substantial earning potential to EV owners. This is because: (a) it has the highest market value for V2G among the different forms of electric power (much higher than peak power, for example), (b) it minimally stresses the vehicle power storage system, and (c) battery-electric vehicles are especially well suited to provide regulation services.

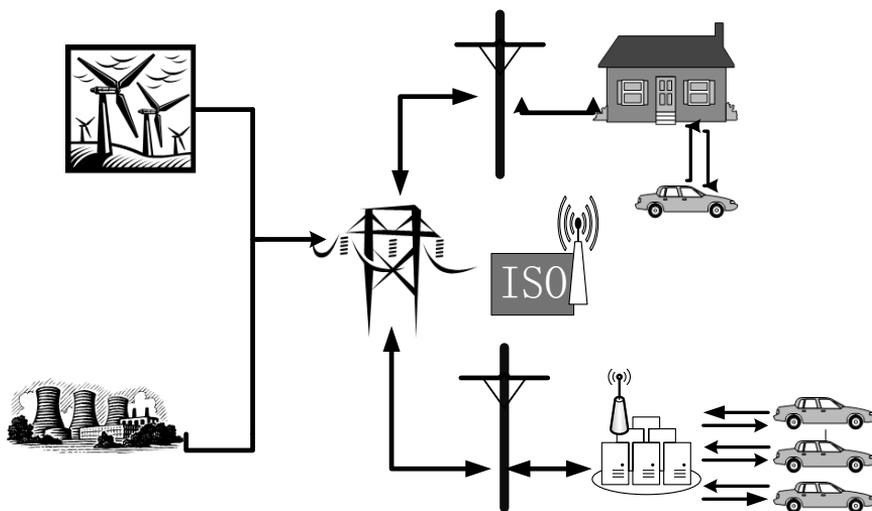


Figure 2.1: Illustrative schematic of proposed power line and wireless control connections between vehicles and the electric power grid, adapted from [12]

As illustrated in Fig. 2.1, the electric vehicles can participate in the regulation services individually or by joining a fleet, the communication can be facilitated by power line and wireless control connections. It is advocated that fleets are more easily accommodated within existing electric market rules, which typically require power blocks of 1 MW. To fulfill the concept of V2G, each vehicle must have three required elements: (a) a connection to the grid for electrical energy flow, (b) control or logical connection necessary for communication with the grid operator, and (c) controls and metering on-board the vehicle. Fig. 2.2 shows

2.1 Management of electric vehicle fleet and their business opportunities¹³

an example of electric vehicle control panel. By predefining the wanted driving distance and the comfortable buffer, the electric vehicles can be connected to the grid and then participate the regulation service market.

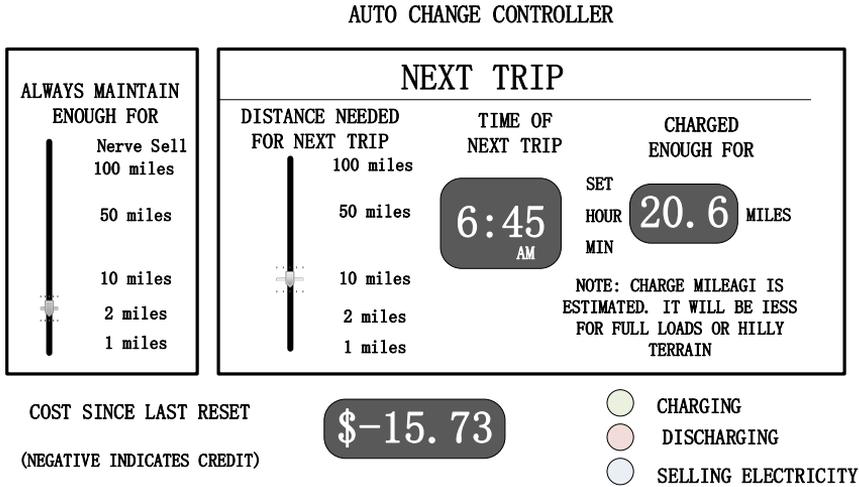


Figure 2.2: Example control panel for a battery electric vehicle, allowing the vehicle operator to constrain charging and discharging by the electric utility, adapted from [11]

It is also learned from the studies [11–14] that important variables for the V2G market are: (a) the value of ancillary services in the area, (b) the power capacity of the electrical connections and wiring, and (c) the kWh capacity of the vehicle battery. The amount of time the vehicles were on the road or discharged did not turn out to be a major variable. The results showed that battery electric vehicles fleets have significant potential revenue streams from vehicle to grid.

Regarding the Danish Power system, Divya et al. [15] carried out a study investigating the feasibility of integrating electric vehicles in the Danish electricity network which is characterized by high wind power penetration. They found that electric vehicles have the potential to assist in integrating more wind power in 2025 when the electric vehicle penetration levels would be significant enough to have an impact on the power systems. Østergaard et al [16–18] shows that intelligent integration of electric vehicles in the Danish power system with high wind power penetration has substantial socio-economic benefits due to its balancing capability.

The studies presented in [12–19] are mainly investigated from the design and analysis perspectives, they gave a good incentive for the electric vehicles to participate into the regulation market. The subsequent work focused on the method development. Rotering and Ilic [20] utilized the dynamical programming to formulate the smart charging problem. They took into account vehicle to grid as a mean of generating additional profits by participating in the ancillary service markets. Based on the data of the independent system operator of California, provision of regulating power substantially improves plug-in hybrid electric vehicle economics and the daily profits amount to 1.71\$, including the cost of driving. Han et al. [21] proposed a fleet operator that manages electric vehicles to provide frequency regulation services, the cost arising from the battery charging and the revenue obtained during the participation is investigated. The question is formulated as an optimization problem and dynamic programming is used to generate the charging profile. Pillai and Jensen [22] investigated the V2G regulation capabilities in the West Denmark power system by using a simplified load frequency control model, in the study, they used an aggregated battery storage model and generators model. The results indicated the regulation needs from conventional generators are significantly minimized by the faster up and down regulation characteristics of the EV battery storage. All these results indicate that it is feasible to participate in the electricity market and provide ancillary service to the grid.

In addition to the focus on providing ancillary services to transmission system operator, several studies investigated the method of maximize the renewable energy penetration with the integration of electric vehicles. Lopes et al. [23] investigated the dynamic behaviour of an isolated distribution grid when wind power and electric vehicles are presented. The objective is to quantify the amount of intermittent renewable energy resources that can be safely integrated into the electric power system with the utilization of EVs' storage capacity. Lund and Kempton [24] investigated the impact of using V2G technology to integrate the sustainable energy system. Two national energy systems are modelled; one for Denmark including combined heat and power (CHP), the other is a similarly sized country without CHP. The model (EnergyPLAN) integrates energy for electricity, transport and heat, includes hourly fluctuations in human needs and the environment (wind resource and weather-driven need for heat). The results indicated that adding electric vehicles and V2G to these national energy systems allows integration of much higher levels of wind electricity without excess electric production, and also greatly reduces national CO₂ emissions.

In above discussion, mostly, these services can be practical in place only provided by a large fleet of electric vehicles. Fleet operator is widely proposed to aggregate the large penetration of electric vehicles in the near future. Alternatively names for an electric vehicle fleet operator are used such as EV virtual power plant, EV aggregator, EV charging service provider or EV service provider. Fleet

2.1 Management of electric vehicle fleet and their business opportunities 15

operators could be independent or integrated in an existing business function of the energy supplier or distribution system operator. For more discussion in term of the fleet operator's roles, the relationships between fleet operators and other actors in a smart grid context, and the communication standards used by the fleet operator and electric vehicles, please refers to paper [A.1](#).

To aggregate and attract the participation of electric vehicles, one incentive for EV owner is to minimize the charging cost, this could be facilitated by optimally charge the electric vehicles when the electricity price is lower. Within this scope, most the work [\[8, 25, 26\]](#) assume that the FO manages the electricity market participation of an EV fleet and presents a framework for optimal charging or discharging of the electric vehicles. In addition, the electricity price of the day-ahead spot market and the regulation market and the driving patterns of the EV fleet are usually assumed to be known by the FO who is assumed to be the price-taker in the electricity market in studies. By implementing linear programming or dynamic programming based cost minimization calculation, an optimal charging schedule for electric vehicles will be generated by the fleet operator. However, Kristoffersen et al. [\[27\]](#) also investigated the possibilities of EV management where the FO has a significant market share and can affect electricity prices by changing the load through charging and discharging. Besides studying the optimal charging from an EV fleet perspective, research in [\[20, 28\]](#) showed how dynamic programming can be utilized by the individual EV controller to make an optimal charging schedule taking into account the electricity market price. In [\[29\]](#), an intelligent charging method is also proposed for individual electric vehicle which responds to time of use price and minimize the charging cost.

In general, these studies focus on manage the electric vehicle centrally. In contrast, although the decentralized control is a relative new application to EV fleet control, there are still a lot of efforts that have been done considering the amount of the articles. One notable study is about the valley filling study which can be seen in [\[30–33\]](#) where market based control strategies are used. In fact, the valley filling charging can date back to 1994 [\[34\]](#) where Ford argues that valley filling would allow the utility to meet anticipated additional loads for EV charging without additions to their existing resource plan. Therefore, he argued, the utility would experience an increase in profits from increased sales and better utilization of their generation equipment. In [\[30–33\]](#), the concepts are similar and the authors assumed that the EVs determines the charging pattern individually and are cost minimization.

In addition to the market based two way communication, by using one way price signal, it means that the EV controller do not need to propose and submit their charging profile to the fleet operator, instead the fleet operator will anticipate their response to the dynamic price. The dynamic price ranges from simple

time-of-use electricity rate [35,36] to more varying hourly prices [37,38]. Both studies [35,36] suggested that the time of use rates can be properly designed to reduce the peak demand as EVs penetrate the vehicle market. However, it is also noted in [36] that the extent to which properly designed rates could assist in maintaining grid reliability will remain open until empirically tested EV owner's price responsiveness through experiment pilots are known. Both studies [37,38] investigated the price elasticity of electricity consumers and these are also the key issues in one-way price signal approach.

2.2 Control strategies for distribution grid congestion management

It is assumed that the distribution network has the capacity to allocate new loads when achieving the objectives discussed above. However, a large penetration of electric vehicles will bring some challenges to the utilities. The challenges usually include peak power issue, grid congestion, power losses, voltage drop et al. Much research has been performed to study the intelligent EV load control and their effect on the grid, which can be dated back to the early 1980s [39]. Heydt [39] argued that load management should be deployed to alleviate peak loading, which is measured in term of load factor improvement. In 1993, Rahman [40] and Shrestha indicated that even low penetration levels of electric vehicles can create new peak loads exceeding the natural peak if sufficient attention is not paid to distribute the charging load throughout the off-peak period. A penetration level of 20% is found to be the upper limit which could be managed by distributing the charging load. Basically, those studies mainly investigated the impacts by adding the new EV loading profile to the already existing load profile and seeing the overall effect and then proposed the load shifting strategy. Recently, more technical parameters such as power losses, power qualities have been used for grid congestion impact studies. In [7, 8, 41, 42], the impacts of electric vehicles on distribution networks are studied, the conclusions are that without charging coordination, the power consumption on a local scale can lead to grid problems. While the coordination of the charging can prevent the grid congestion, reduce the power losses, improve power quality etc.

In order to eliminate the grid congestions, three overall approaches have been identified in [43] to handle the integration of distribution grid congestion and electric energy balance. Three listed approaches include integrated process, stepwise process form first electric energy balance, then grid congestion, and stepwise process form first grid congestion, then electric energy balance. Advantages and disadvantages of the three listed options are discussed in report [43]. Different types of approaches including payment for the right to use capacity,

variable tariffs, direct control, a bid system etc., are discussed in the report. In the following, some articles are presented which can elaborate the discussion in [43] starting with the direct control, then with the market based control and finally the price control method.

In study [44], the model being tested by Ericsson and partners is shown in Fig. 2.3. With this proposal, The charge schedule can thus be selected directly by the electricity utility to meet the owner’s or driver’s requirements, as well as spreading the demand over the course of the night. Further discussion are made on the enabling technologies in the study.

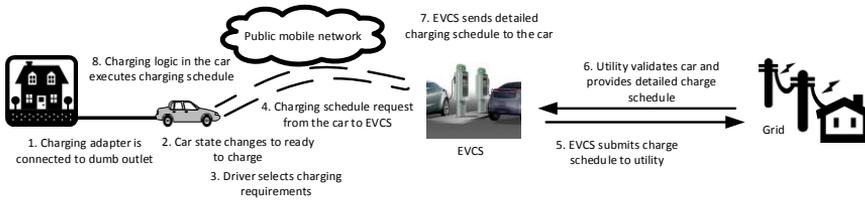


Figure 2.3: The electric vehicle charging system, adapted from [44]

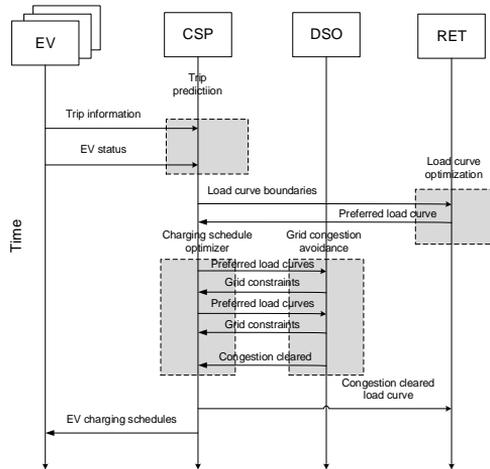


Figure 2.4: The flow of information between the relevant actors, adapted from [8]

In [8], a complex scheduling problem involving the EV owners, the FO (charging

service provider (CSP in the article) and the DSO is analyzed. The approach requires a complex interaction between the DSO and the CSP, on each interaction, the CSP will get a specific grid constraint from the DSO and add it into the EV charging cost minimization problem. The results show that both the CSP and the EV owners can achieve the objectives of minimizing charging costs and fulfilling driving requirements without violating the grid constraints. Fig. 2.4 illustrates the information flow between the relevant actors.

Lopes et al. [45] proposed a conceptual framework consisting of both a technical grid operation strategy and a market environment to integrate electric vehicles into the distribution systems, as shown in Fig. 2.5. The fleet operator is proposed to manage the electric vehicles and the fleet operators will prepare the buy/sell bids into the electricity market. Having this defined, a prior interaction with the DSO must exist to prevent the occurrence of congestion and voltage problem in the distribution network. The smart charging algorithm is mainly designed for the operation of the DSO which can maximize the density of the EV deployment into the grid.

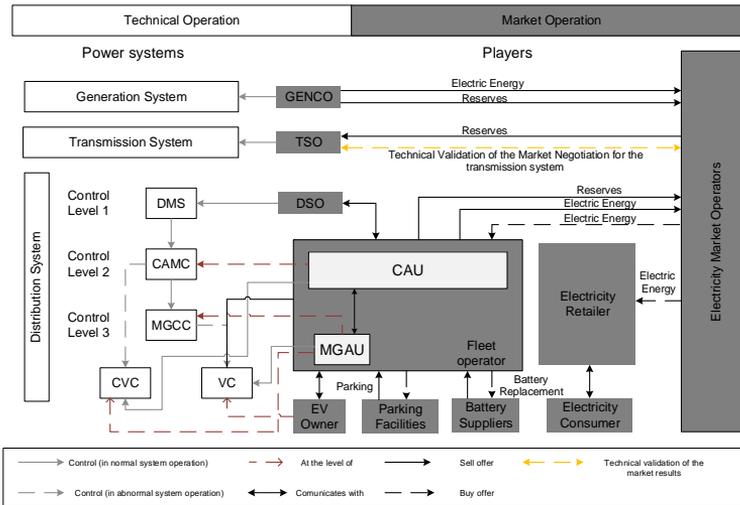


Figure 2.5: Technical management and market operation framework for EV integration into electric power systems, adapted from [45]

Alternatively, several ways of solving the congestion problem have been suggested from market perspective. In study [46], Ipakchi pointed out that a transition from a traditional view of power systems operation towards smart grid operating paradigm is needed. It is also pointed that the higher penetration of distributed resources will require a greater attention to distribution conges-

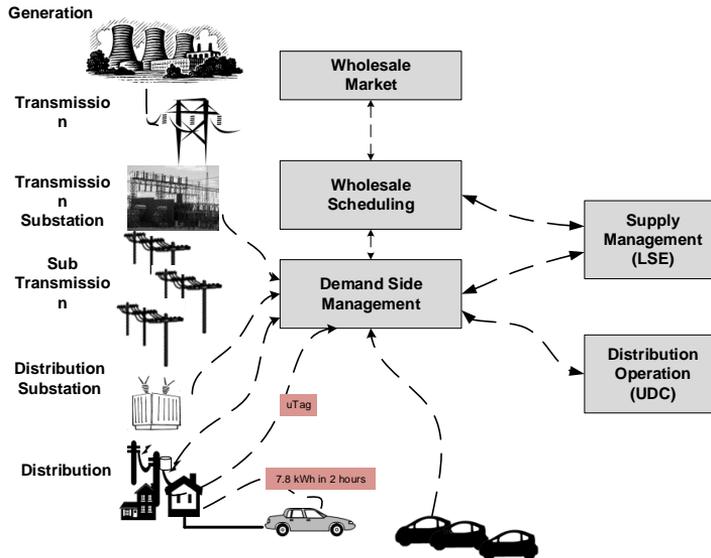


Figure 2.6: Concept of micro-transactions for management of charging loads of plug in electric vehicles, adapted from [46]

tion issues and the need for improved distribution automation and distribution management capabilities. A transactive based approach is proposed to solve the problems, Fig. 2.6 illustrates the concept. In the concept, A plug-in electric vehicle requests using 7.8 kWh of charging energy over the next two hours. This request can be presented as a demand transaction and sent to a Demand-Side Management application operated by the utility distribution company. Knowing the service delivery point to which the car charger is connected to, this application will check the available capacity of the secondary distribution transformer, lateral and feeder circuits and determine if this additional load will not impact the circuit reliability and cause any adverse phase imbalances. The Demand-Side Management application will then schedule the charging for the requested time period. At the same time, the application may receive many more information such charging requests that have to be checked, and in aggregate they have to be coordinated with wholesale scheduling at substation supplying the feeders to ensure adequate supply. Each of these actions could be modeled as a transaction between a consumer system, a utility decision support system, distribution field equipment and supply scheduling system in an aggregate form.

Transactive control is a kind of market based control technology and considered as a specific instantiation of a GridWide Architecture Council [47,48]. The intent

of transactive control is to standardize a scalable, distributed mechanism for exchanging information about generation, loads, constraints and responsive assets over dynamic, real-time forecasting periods using economic incentive signaling. Fig. 2.7 from [49] lists the key issues of the concept. It presented an example that precise, stable control of congested grid nodes can be derived from (1) customer price-responsive controls that (2) express their available flexibility to (3) a price discovery mechanism. In other words, the GridWise initiative have adopted an agent based computational economics modeling for incorporating the market mechanisms that allow the system to evolve over time in response to market dynamics.

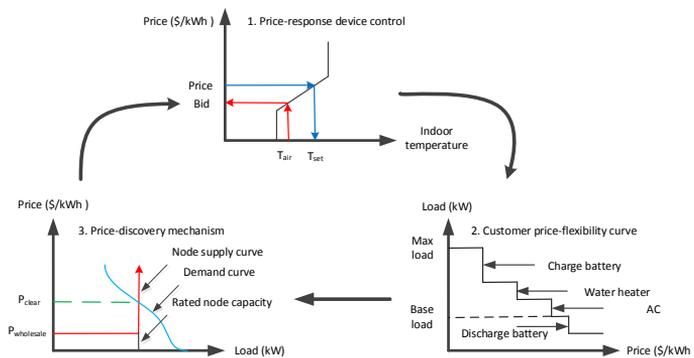


Figure 2.7: Key issues in a transactive control, adapted from [49]

PowerMatcher ¹ is another good example of a market-based control concept for supply and demand matching in electricity networks. It is discussed in [50] that the PowerMatcher technology is based on multi-agent systems and electronic markets which form an appropriate technology needed for control and coordination tasks in the future electricity network. Background theories used are control theory and micro-economics, unified in market-based control theory and it is presented in [51], one of the conclusions from the study is that computational economics with dynamic pricing mechanisms are able to handle scarce resources for control adaptively in ways that are optimal locally as well as globally. The basic structures and agents are illustrated in Fig. 2.8, for the roles and functions of the agents, please refer to PowerMatcher website.

In addition to the proposed market based approach, price control is also extensively discussed in several studies [9, 43, 52]. Several tariff signals including time

¹<http://www.powermatcher.net/>

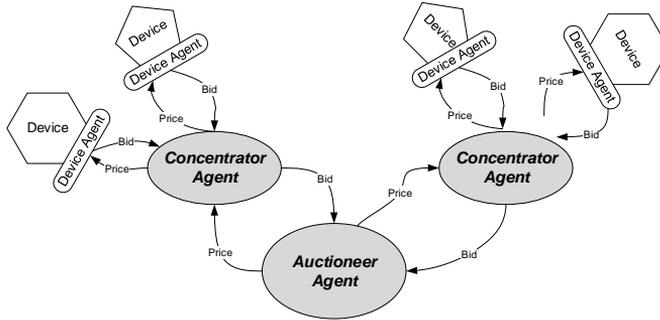


Figure 2.8: Concept of PowerMatcher technology, adapted from [50]

of use tariffs, critical peak pricing, variable tariff and dynamic tariff have been general discussed and compared in [43, 52]. The comparison are discussed from the activation, timing of price determination, tariff characteristics, price variations, advantages and disadvantages perspectives. In both reports, a bid-less, day-ahead setup market model is discussed, Fig. 2.9 illustrates the model. The model has been tested in study [9] and the results indicated that it could be useful to alleviate the grid congestion.

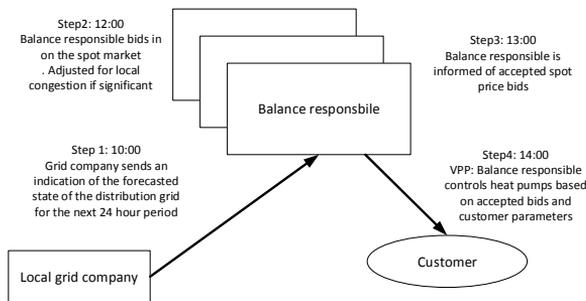


Figure 2.9: A bid-less day-ahead setup market model, adapted from [52]

2.3 Multi-agents systems for smart distribution grid operation and simulations

Multi-agent systems (MAS) have been widely proposed for several studies in the context of power systems, such as power system restoration [53], power system operation and control [54], and electricity markets modeling and analyzing [55, 56]. More recently, the multi-agent concept is proposed for distribution system operation and control [57–61], especially, considering the capacity management with a large penetration of electric vehicles [62, 63] and the capacity management with more general loads [64].

The authors [62] proposed a distributed, multi-agent electric vehicle charging control method based on Nash certainty equivalence principle that considers distribution network impacts. Four types of agents are included in the study, EV aggregator agent, regional aggregation agent, microgrid aggregation agent and cluster of vehicles controller agent, and vehicle controller agents. In the non-cooperative, dynamic game, all the vehicles controller agents decide the strategy that minimizes his own objective functions. The up-level agents coordinate vehicles controller agents' charging behaviour by changing the price signal. The price signal is a reflection of congestion conditions. The results indicate that the proposed approach allocates electric vehicle energy requirements efficiently during off-peak hours which achieves effectively valley filling and also leads to maximization of load factor and minimization of energy losses. The authors in [63] used the MAS to design a distributed, modular, coordinated and collaborative intelligent charging network with the objective of pro-actively scheduling the charging of up to fifty electric vehicles as well as eliminating the grid overloading issue. The study mainly considered how the electricity is distributed to the multiple charging point agent under one local power manager agent and this is done by an auction mechanism. Each charging point agent makes a bid for the energy in the next 15 minutes until it get the desired state of charge of the battery, then the local power manager agent sorts out the orders to determine which electric vehicle can be charged during the time slot. In [64], an active distribution network (ADN) is presented with its actors and their objectives. The multi-agent technology is proposed for the normal operation of the ADN, in which the auctioneer agent (placed at the MV/LV transformer) communicates with the device agent by sending the price signal and receiving the bid curve. Further on, capacity management is investigated by transforming the bid curves of the device agents.

In general, the above studies [62–64] adopted an agent-based computational economics modeling ² for incorporating market mechanisms to allocate the grid

²Please see the discussion regarding GridWise and PowerMatcher concept review.

capacities and the results indicated the agent-based market mechanisms solve the grid congestion efficiently. However, in term of simulations, much work needs to be studied, as discussed in [57], currently available software tools provides either modeling of dynamic electric power networks or implementation of intelligent system techniques such as intelligent agents. Therefore, a software platform which can simulate multi-agents based control strategies that incorporates power system dynamics and intelligent control strategies is highly required. In [57], the author developed a software platform based on the integration of JADE and DigSilent PowerFactory which can enables design, test, and verification of agents based control technologies. Besides, in [65], a simulation framework named mosaik is developed to facilitate the simulations running several separately software together, the purpose of the developed framework is to reuse existing models in a common context to simulate complex smart Grid scenarios in order to evaluate control strategies, such as agent based control strategies.

2.4 Summary

The overall state of the art of the technology for capturing the business opportunities provided by electric vehicle fleet is quite feasible and promising. But as a commercial actor, which control strategies is optimal, and what is the implications for choosing one control strategies to manage the electric vehicle fleet? At the same time, the commercial actor needs to coordinate with the distribution system operator to prevent the congestion before bidding into the conventional markets, several approaches have been reviewed and there is a need to devise the suitable one for this context. In addition to this, to simulate and evaluate the control strategies developed for distribution grid congestion management with EV integration, whether multi-agents based technology is a good approach and if yes, how to develop a multi-agent systems? The need to answer such questions have motivated the choice of research topics for this thesis.

Optimization and control for integrating electric vehicles

In this chapter the main results concerning the first research topic are summarized. The main results and details have been published in separate papers [A.1](#), [A.2](#), [A.3](#), and [A.4](#) that are included in appendices of this report. The chapter starts with some background knowledge including the electricity market, battery modeling, and vehicle driving pattern, because these are the primary inputs that are needed in an electric vehicle optimal charging problem. Then, we present the main results including a comprehensive review on the three control strategies developed for electric vehicle integration and four developed methods during the PhD study, i.e., problem formulations of electric vehicle optimal charging schedule by linear programming, dynamic programming, mix integer linear programming and statistic modeling based techniques.

3.1 Background knowledge

3.1.1 Nordic electricity market

In the Danish Edison project ¹, an overall discussion is given on the current Nordic electricity market and how the electric vehicles can be integrated into the current and future markets [[43](#),[66](#)]. The reader is referred to the two reports for more details. Here we briefly introduce the spot market and the regulation market since they are most relevant to the thesis.

¹<http://www.edison-net.dk/>

3.1.1.1 Spot market

In the Nordic electric power market, energy is exchanged by direct trading amongst player (bilateral trade) and via the Nordic power exchange, NordPool. There are two main markets for energy exchange within NordPool that are Elspot for day-ahead trading and Elbas for the balancing market. Elspot is a day-ahead market where hourly exchanges are traded. The way of calculating the price is called double auctions, as both the buyers and the sellers have submitted bids. At noon, NordPool Spot's computer in Oslo starts calculating the day-ahead price. Having finished the calculation, NordPool Spot publishes the prices. At the same time, NordPool Spots reports to the participants how much electricity they have bought or sold for each hour of the following day. These reports on buying and selling are also sent to the TSO in the NordPool spot area. The TSO use this information, when they later calculate the balancing energy for each participant. Apart from calculating day-ahead prices, the Elspot market is also used to carry out day-ahead congestion management in the Nordic region. The day-ahead congestion management system is called market splitting. More discussion regarding market splitting can be seen in [67, 68].

3.1.1.2 Regulating power market

The regulating power market is managed by the transmission system operator ² in order to obtain ancillary services in the transmission grid. It may happen that the consumption exceeds (or lags behind) the generation. In this case, the frequency of the alternating current will fall to (exceed) a value below (above) 50 Hz. As renewable energy will become an increasing important resource for reducing emissions from fossil fuels, production will become more intermittent, and therefore it is anticipated that the need for regulating power will increase [43, 66].

3.1.2 Battery modeling

Basically, there are two ways to model the charging characteristics of electric vehicles, i.e., the battery. One is the individual battery pack model, another is the aggregated or cell based model. For simplicity, most of the studies reviewed considered it as a battery pack when investigating the optimal charging or discharging problem. Currently, most battery model studies focus on three different characteristics [69, 70]:

²<http://www.energinet.dk/EN/El/Systemydelse-for-el/Sider/Systemydelseforel.aspx>

- The first and most commonly used model is termed as a performance or a charge model and focuses on modelling the state of charge of the battery, which is the single most important parameter in system assessments.
- The second type of model is the voltage model, which is used to model the terminal voltage so that it can be used in more detailed modelling of the battery management system and the more detailed calculation of the losses in the battery.
- The third type of model is the lifetime model used for assessing the impact of a particular operating scheme on the expected lifetime of the battery.

The present study mainly focuses on smart charging of electric vehicle and therefore we present more introduction on the first characteristic, i.e., modeling the state of charge of a battery during the operation.

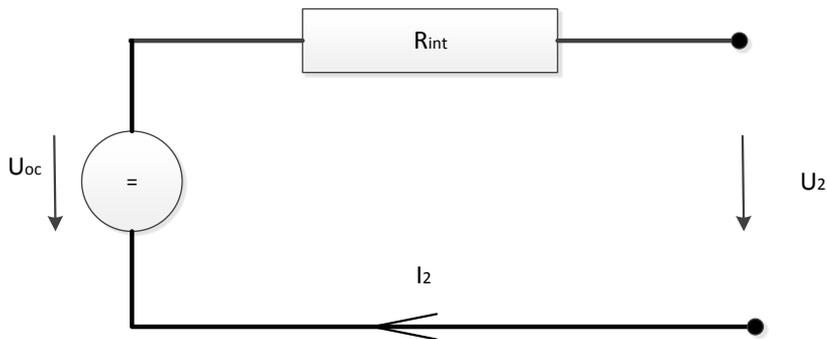


Figure 3.1: Equivalent circuit of a battery

A basic physical model of a battery can be derived by considering an equivalent circuit of the system like the one shown in Fig. 3.1. The steady state battery equivalent circuit has been applied mainly for various lead acid batteries, but also for nickel cadmium, nickel metal hydride and lithium-ion batteries. In this circuit, the battery is represented by an voltage source in series with an internal resistance. Kirchoff's law for the equivalent circuit yields the following equations:

$$U_{oc}(t) - R_{int}(t) \cdot I_2(t) = U_2(t). \quad (3.1)$$

Both the voltage source $U_{oc}(t)$ and the internal resistance $R_{int}(t)$ are dependent on the state of charge (soc)³ of the battery.

Normally, two ways are used to characterize the capacity of a battery, kWh and Ah⁴. If the dynamics of the state of charge of the battery is calculated by adding kWh into the available capacity, it usually starts with the calculation of the internal power of the battery which can be approximated linearly or nonlinearly⁵ with the external charging power, like the one presented in the study [8,25], also described in the section B.1. The studies [8,25] have shown that the difference between the two charging schedules using linear approximation and nonlinear approximation (second-order Taylor series expansion) is minor and indicates that the linear approximation is sufficient and the benefit of using a nonlinear approximation does not justify the increase in computation time. If the dynamic of the state of charge of the battery is characterized by the calculation of the dynamics of the electric charge, like the one used in study [20,28], also described in the section B.1, dynamic programming is usually used to formulate the optimal charging of electric vehicle.

3.1.3 Driving pattern and associated electricity consumption

The analysis of driving pattern can be divided into two main directions:

- Utilization of electric vehicles, in other words, when and how long the electric vehicle will be used in the next scheduling period, e.g., 24 hours in the present study. This is because when and how long decide the energy that need to be procured or charged for the next scheduling period.
- Location of electric vehicles when charging and how many of them will be charged at a time, because the location of the electric vehicles inside the network will determine where the grid will be possibly congested.

In most studies [8,20,25], the authors assume that the fleet operator knows the users' driving patterns and thereby can forecast the electricity demand. There are few studies on investigating the driving pattern. Kristoffersen et al. [27]

³Usually, the abbreviation for state of charge should be capital letter, i.e., SOC. Here, we use 'soc' because it will be used as a variable in section B.1.

⁴kWh=Ah*voltage

⁵Using linear approximation, the internal power is assumed to be equal to the external power; using nonlinear approximation, the internal losses in the battery can not be neglected, therefore, the internal power is not equal to the external power

investigated a method to construct driving patterns from the historic data in Danish case. By clustering the survey data on the vehicle fleet in Western Denmark (January 2006-December 2007), representative driving patterns for each vehicle user are constructed. S. Shahidinejad et al. [71] developed a daily duty cycle which provides a complete data set for optimization of energy requirements of users. And furthermore, this information is used to analyse the impact of daytime charging by a fleet of plug-in electric vehicles on the electric utility grid that may create a peak demand during the day to be met by the local utility grid. Normally, intra city or short term driving patterns are largely predictable due to fixed working hours and fixed business schedules and routes.

In the present thesis, the driving pattern is based on the 2003AKTA Survey [72], where 360 cars in Copenhagen were tracked using GPS from 14 to 100 days. Each data file includes starting and finishing time, and the corresponding duration and distance. The original data is transferred into 15 minutes interval driving energy requirements based on the assumption of that an electric vehicle will use 15 kWh per 100 km (typically, the number ranges from 11 kWh to 18 kWh per 100 km). Some artificial driving data of the electric vehicles have been generated from the database based on some facts observed in study [73]. In [73], a Danish driving pattern analysis is presented which listed that the average driving distance in Denmark is 42.7 km per day. With the assumption of 0.15 kWh/km for energy used per km of electric vehicles, one can deduce that the monthly energy requirement for an electric vehicle will be around 192 kWh ($42.7 \text{ km} \cdot 30 \cdot 0.15 \text{ kWh/km}$). Using Nissan Leaf (EV battery capacity is 24 kWh) as an example, this would imply that the users need to charge the Leaf around 8 times ($192 \text{ kWh} / 24 \text{ kWh}$). However, owners will rarely fully discharge their Leaf before recharging it. For discussion purposes, it is assumed users will charge the electric vehicle 20 times per month which implies that each time 9.6 kWh energy will be procured. In the current case, they would imply around five hours charging ($9.6 \text{ kWh} / 2.3 \text{ kW}$). Using 9.6 kWh as an average number, the driving data is randomly chosen and transferred into a 15 minutes interval driving energy requirements.

3.2 Main results

3.2.1 Three control strategies for integrating electric vehicles

As discussed in paper A.1, also reviewed in section 2.1, several business opportunities provided by EV fleet have been identified such as providing ancillary

services to transmission system operation and storing service to renewable energy producers. To capture the business opportunities, fleet operator has been proposed to manage EVs. Fleet operator [74, 75] could be independent or integrated in an existing business function of the energy supplier. Furthermore, Fleet operator needs to coordinate with the distribution system operator to manage the congestions in the distribution network. In principle, two types of control architectures can be used by FOs when aiming at realizing the business opportunities, named centralized and decentralized control. In both control architectures, the grid constraint from the distribution grid should be considered.

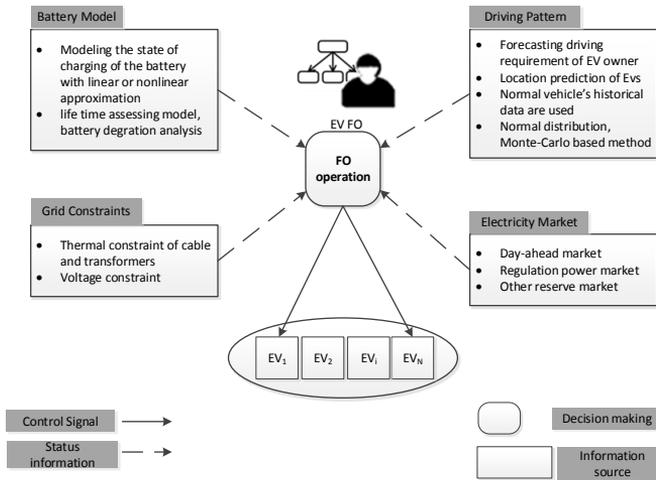


Figure 3.2: Centralized control: primary inputs and output of the electric vehicle fleet operator

In centralized control, electric vehicles are aggregated and controlled by fleet operator directly. e.g., by dictating the charging schedules. In decentralized architecture, the control is implemented in the form of price signal, i.e. the individual EV optimizes the charging schedule based on the electricity price information made available to them either from FO or the utility. Figure 3.2 depicts the mainly four inputs when making the control strategies in the case of centralized control. The FO obtains all the relevant information including the battery model, the driving patterns, the grid constraints and the electricity price and centrally makes the charging schedule for each EV. In contrast, in the context of decentralized charging, the FO uses price signal to coordinate the EV users' charging behavior. Two methods of implementing decentralized charging control are summarized. The scheme of the information flow in decentralized

charging control is presented in Fig 3.3. In Fig. 3.3 (a), the basic idea for market based control strategy is that EVs update their charging profiles independently given the price signal; the FO guides their updates by altering the price signal. Several iterations are usually required for the implementation. In Fig. 3.3 (b), the price control method requires FO to predict the users' response to the prices. The price signal can be designed simply as time-of-use price or as dynamic prices.

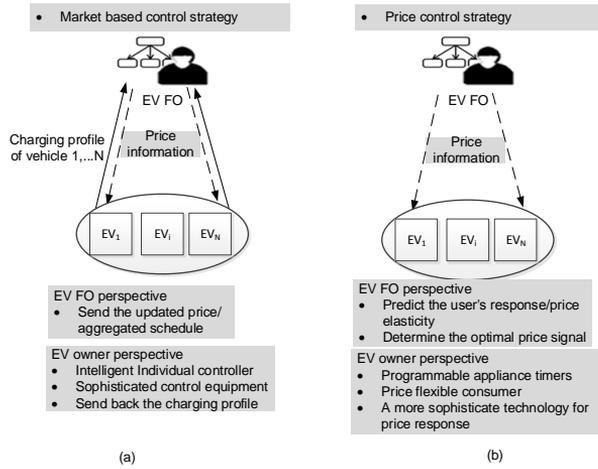


Figure 3.3: Decentralized control: a schematic view of the information flow below the fleet operator and the electric vehicles

3.2.2 Formulation of the optimal charging of electric vehicles by centralized control architecture

In the following, we introduce the method to formulate the optimal charging schedule of electric vehicles based on linear programming, dynamical programming, and mixed integer programming techniques.

3.2.2.1 Linear programming based optimal charging schedule generation

As explained in section 3.1.2, this study uses the linear approximation method. Linear programming approach is utilized to optimize the charging schedule of an EV fleet both taking into account spot price and individual EV driving requirement with the goal of minimizing charging costs. A simplified version of Fig. 3.2 is used to guide the control algorithm design. The charging schedules of the EV fleet are optimized individually and then each EV' schedule is summed, since it is considered that the individual's driving requirements should be fulfilled and calculated separately. The formulation is shown in the following:

$$\text{minimize } \sum_{i=1}^{N_T} \Phi_{j,i} \cdot P_{j,i} \cdot t, \quad j = 1, \dots, N_k^E$$

subject to

$$\begin{cases} SOC_{0,j} + \sum_{i=1}^{n_T} P_{j,i} \cdot t_{j,i} \geq SOC_{Min,j} + \sum_{i=0}^{n_T-1} E_{d,i+1} \\ SOC_{0,j} + \sum_{i=1}^{n_T} P_{j,i} \cdot t_{j,i} \leq w \cdot E_{cap,j} + \sum_{i=2}^{n_T+1} E_{d,i-1} \\ 0 \leq P_{j,i} \cdot t_{j,i} \leq P_{max,j} \cdot t_{j,i}, \quad i = 1, \dots, N_T \end{cases} \quad (3.2)$$

With the above optimization problem, the FO can generate a unique energy schedule for EV owner; the sum of the individual EV energy schedule will be denoted as $P_{k,i}^E$, and

$$P_{k,i}^E = \sum_{j=1}^{N_k^E} P_{j,i}, \quad k = 1, \dots, N_B, \quad i = 1, \dots, N_T,$$

where

N_k^E Number of EVs under FO k .

N_T Number of time slot in the scheduling period.

N_B Number of FOs.

j Index for the number of EVs under each FO, $j = 1, 2, \dots, N_k^E$.

i Index of time slot in the scheduling period, $i = 1, 2, \dots, n_T, \dots, N_T$.

k Index for the number of FOs, $k = 1, \dots, N_B$.

- $\Phi_{j,i}$ Predicted day-ahead electricity market price vector.
- $P_{j,i}$ Decision variable vector.
- t Length of each time slot.
- $P_{k,i}^E$ Power requirements of EVs of each FO in each time slot.
- $SOC_{0,j}$ Initial state of charge of individual EV.
- $SOC_{Min,j}$ Recommended minimum state of charge of the EV.
- E_d The predicted individual EV owner's driving requirement.
- $P_{max,j}$ Charge rate in term of energy of individual EV.
- $w * E_{cap,j}$ Recommended maximum state of charge of the EV, where w is the parameter which express the charging behavior of the battery of the EV is a linear process, $E_{cap,j}$ is the capacity of the battery of the EV.

In Eq. (3.2), the first constraint means that the available energy in the battery should be greater than or equal to the energy requirement for the next trip. The second constraint indicates that the available energy in the battery should be less than or equal to the power capacity of the battery. The third constraint represents that the charging rate is less than or equal to its maximum power rate of a charger. The physical meaning of the decision variable vector $P_{j,i}$ is to make a decision to distribute/charge the power on the certain time slots, where the charging cost can be minimized. The solutions of some numerical studies are presented in paper [A.2](#), [A.6](#).

3.2.2.2 Dynamic programming based optimal charging schedule generation

As explained in section [3.1.2](#), the study presented in paper [A.3](#) considers the dynamics of the state of charge of the battery using electric charge. The control architecture used in the study is also a simplified version of the one shown in Fig [3.2](#). For the day-ahead scheduling, the time horizon $[0, N]$ of a day is discretized into equidistant time intervals $[k, k+1]$ with $k = 0, \dots, N-1$. It is assumed that the time interval is Δt . This problem is addressed by considering the following discrete system which describes the battery:

$$x_{k+1} = T(x_k, u_k, k) \quad (3.3)$$

State variable x_k represents the state of charge of the battery at time k . x_k is not only discrete in time (index k) but also in value. Any value has to be included in the predefined set X , which can be calculated by a function of charge Q_k and total capacity Q_{max} .

$$x_k = \frac{Q_k}{Q_{max}} \quad (3.4)$$

u_k in equation 3.3 is the control variable, which is dimensionless and discrete. u_k is multiplied with the maximum available charge power (P_{max}) when electric vehicle is connected with the grid. The values of u_k are fixed at 0 when driving, while these values range from 0 to 1 when electric vehicle is connected to the grid. If U_{plug} is the set that covers all possible values of u_k , its discretization may be described as follows:

$$u_k = \begin{cases} u_k \in U_{plug}, & k \in K_{plug} \\ u_k = 0, & k \in K_{driv} \end{cases} \quad (3.5)$$

K_{plug} is a set of indices k within the time periods where the vehicle is plugged in, while K_{driv} refers to the driving intervals. The summation of the number of elements in K_{plug} and K_{driv} is N , the total number of time intervals. Any index k in K_{plug} or K_{driv} has to be element of the predefined set K .

$$k \in K = \{K_{plug}, K_{driv}\} \quad (3.6)$$

A specific control strategy is represented by

$$u = \{u_0, u_1, u_2, \dots, u_{N-1}\} \quad (3.7)$$

Any value of u_k has to be element of a predefined set U , which is known as the set of admissible decision. The total cost of a sequence, f_0^U , is given by the cost of the final step, $f_N(x_N)$, plus the cost for all other previous steps, $v_k(x_k, u_k, k)$, then we have:

$$f_0^U(x_0) = f_N(x_N) + \sum_{k=1}^{N-1} v_k(x_k, u_k, k) \quad (3.8)$$

The optimal control strategy $u^* = \{u_0^*, u_1^*, u_2^*, \dots, u_{N-1}^*\}$ minimizes the cost function 3.8 and can be determined by the dynamic programming. For case studies and their solutions, please refer to paper A.3.

3.2.2.3 Mixed integer linear programming based optimal charging and discharging schedule making

In order to investigate the economics of vehicle to grid technology, e.g., providing ancillary service to the regulating power market, four different charging schemes

including night charging, night charging with V2G, 24 hour charging and 24 hour charging with V2G are studied in paper A.4 to compare their annual cost.

Two steps are used in the study. In the first step, the numerical comparison of four charging schemes only includes charging cost (charging cost is equal to cost of electricity procured minus profits of implementing V2G). This is obtained by solving a mixed integer programming problem with the purpose of minimizing the charging cost by taking into account the users' driving needs and the practical limitations of the EV battery (capacity of the battery, recommended state of charge range). A formulation of the problem is shown below:

$$\min \sum_{i=1}^N \left\{ \Delta E_c(i) \cdot \Phi(i) \cdot \frac{u_1(i)}{\eta_c} + \Delta E_d(i) \cdot \Phi(i) \cdot u_2(i) \cdot \eta_d \right\}$$

subject to

$$\left\{ \begin{array}{l} E(i) = E_0 + \sum_{k=1}^{k=i} \{ \Delta E_c(k) \cdot u_1(k) + \Delta E_d(k) \cdot u_2(k) - E_d(k) \cdot u_3(k) \} \\ \delta_{min} \cdot E_{cap} \leq E(i) \leq \delta_{max} \cdot E_{cap} \\ E_d(i+1) \cdot u_3(i+1) \geq E(i) \\ 0 \leq \Delta E_c(i) \leq P_{c,max} \cdot \eta_c \cdot \Delta t \\ -\frac{P_{d,max}}{\eta_d} \leq \Delta E_d(i) \leq 0 \\ u_1(i) + u_2(i) + u_3(i) = 1 \end{array} \right. \quad (3.9)$$

where $\Phi(i)$ is the electricity price and $E_d(i)$ denotes driving energy requirements. The decision variables $\Delta E_c(i)$ and $\Delta E_d(i)$ represent the energy charged into and discharged from the battery in each time interval respectively, while the other three binary variables $u_1(i)$, $u_2(i)$, $u_3(i)$ indicate the on/off status of charging, vehicle to grid (discharging), and driving for each corresponding time interval. To facilitate the formulation, an intermediate variable $E(i)$ is introduced representing the energy level of the battery at the end of each time interval. Parameters E_{cap} and E_0 represent the nominal energy capacity and the initial energy of the battery in the planning period, while the charging and discharging efficiency are represented by η_c and η_d . The maximum power exchanged between the EV inverter and the electrical grid are expressed by $P_{c,max}$ charging and $P_{d,max}$ discharging respectively, which constrains the maximum energy exchanged between the electric vehicle and the grid. Concerning battery life, δ_{min} and δ_{max} are further introduced to represent the manufacturer recommended state of charge (SOC) range. Explanations of the inequality constraints can be found in section 3.2.2.1. Based on the model, optimal charging plans with 5 minutes resolutions are derived.

In the second step, or the post processing stage, the rainflow counting algo-

rithm is implemented to assess the lifetime usage of a lithium-ion EV battery for the four charging schemes. By applying the rainflow counting algorithm to the monthly charging profiles calculated in the first step, and take the relationship between the number of cycles and depth of discharge, the battery lifetime consumption for different charging schemes are calculated. (For the details of rainflow counting algorithms, please refer to paper A.4.) Finally, a simple approach is introduced to roughly estimate the annual cost for different charging schemes:

$$C_{ann} = (C_{capacity} + C_{charging})/L_{exp} \quad (3.10)$$

where $C_{capacity}$ and $C_{charging}$ represent the capital cost of the battery and charging cost incurred during the battery lifetime respectively, and L_{exp} indicates the expected lifetime for different charging schemes. This complete the calculation of the annual cost. The study illustrated that the night charging scheme is the cheapest solution among four different charging schemes. For parameters values and calculation results etc., they are presented in paper A.4.

3.2.2.4 Algorithm comparisons

Together with the observations from other research, the readers are referred to paper A.1, table 3 to find the comparison among the chosen algorithms such as linear programming, dynamic programming, quadratic programming, and stochastic programming. The comparisons include the computation time, the certainty of performance, and the applicability.

3.2.3 Formulation of the optimal charging of electric vehicles using decentralized control architecture

For the decentralized control architecture, price control is studied. As illustrated in Fig. 3.3 (b), the price control method requires FO to predict the users' response to the prices. In order to study how the price can regulate the EV user's charging behavior, a statistical model of demand elasticity proposed in [38] is used for this study. In the model, the marginal utility function of the loads is realized by the following parametric stochastic process:

$$r(t) = \begin{cases} \beta - \delta(t - \alpha), & \alpha \leq t \leq \alpha + \gamma \\ 0, & otherwise \end{cases} \quad (3.11)$$

where $\alpha, \beta, \gamma, \delta$ are random variables that describes the different characteristics of utility function as follows:

- a) α stands for the time slot that a task is initially requested, which also reflects the task distribution.
- b) β is the initial marginal utility, which stands for the magnitude of the marginal utility.
- c) γ is the tolerable delay, which determines the maximum delay that a user can tolerate to finish a task.
- d) δ means the utility decay rate, which represents the cost of inconvenience by the delay.

Under this model, the scheduling of each individual task is now a random event whose probability distribution is controlled by the stochastic process $r(t)$. The aggregated demand curve can be estimated through expectation with respect to the distribution of $r(t)$. Note that some assumptions have been made before, such as the time period of the scheduling is divided into T time slots, the total M individual tasks $m : m = 1, \dots, M$ of different electric vehicles that are to be initialized by all the users within the scheduling period, and each task will consumer xm kWh energy, all in all, X_0 is the total energy consumption to be scheduled in the target scheduling period. Furthermore, it is assumed that each task can be completed within one time slot; therefore, tasks that have duration longer than one time slot will be decomposed into multiple tasks that are considered independently. A case study is performed and the simulations are presented in section B.2.

3.3 Summary and discussions

This chapter mainly investigates the control strategies for commercial actors, such as fleet operators. However, some methods can also be used by the utility to coordinate the charging profiles of electric vehicles. The control strategies investigated including centralized control and price control. For centralized control, three algorithms have been used for the methods development. It is recommended that linear programming based technique is considered for characterizing the optimal charging scheduling problems. The recommendation is based its overall performance and its fast computational time. Regarding price control, it is demonstrated that price signal is an effective way of regulating the charging behavior of electric vehicles, however, more research is needed in designing a proper rate which can mitigate the uncertainty caused by using the price control.

Considering fleet operators' practical operations, it is assumed that EVs need to subscribe to one FO, maybe in the form of signing a contract that is valid for certain time period. Such subscription would possibly following the existing geographical areas, i.e., the neighborhood supplied by one FO, under one substation. The mobility of electric vehicle, in such context, will also require the roaming-related agreement/standards among different FOs as well as an standardized information and communication infrastructure, in order to make sure the fleet operators can access the EV information immediately when the electric vehicles switch fleet operators.

In order to generate an optimal charging schedule, forecasted electricity price and predicted EVs driving pattern are essential, fortunately, they are predictable. Among the presented control strategies, it depends on the context to choose the right method (suppose the electric vehicles can be either direct controlled or be price coordinated). Some business scenarios are considered here:

- In scenario 1, FOs only participate in the day ahead market with the objective of minimizing the energy cost, it is recommend that direct control is most efficient and economical, together with the linear programming based technology.
- In scenario 2, the FO would like to participate in both the day-ahead spot market and the regulating power market, direct control is still our first option considering it high certainty in term of bidding resources preparation and activation.
- In scenario 3, the FO will help the DSO to reduce the peak load, it is suggested that either direct control or price control can be used, each method has its advantages and disadvantages, for example, price control is easy to be implemented comparing to direct control while direct control can ensure a low risk.

Such illustrative scenarios are presented to show that although the options for fleet operators are not one and only, the difference does exist considering different questions/contexts.

Market based control for distribution grid congestion management

In this chapter the main results concerning the second research topic are summarized. The main results have been published in separate papers [A.5](#), [A.6](#), [A.7](#), [A.8](#), included in appendices of this report. The chapter starts with the formulation of congestion problems in distribution network. Then, the chapter introduces the background knowledge for market based control method which is the solution for distribution grid congestions in the present thesis. Finally, the chapter presents the main results of the second research topic.

4.1 Formulation of the congestion problems in distribution network

In this section, first, the impact of electric vehicle's charging as an extra load on the distribution grids is illustrated. Then, congestions management in distribution network operation and its enabling functions in a smart distribution grid paradigm are presented.

4.1.1 Electricity consumption by electric vehicles and its impact on the distribution grids

It is mainly regarded that electric vehicle as a kind of new load will mainly bring challenges to the distribution network level such as congestions and voltage drops, while some discussions are taken from the perspective that simultaneous charging of electric vehicle at system peak could result in shortage or create a need for large new investment in generating capacity. To explain these points, we provide some illustrative calculations based on the parameters or estimated numbers related to Danish power systems [2,73,76,77]. Report series [2,76] published by the Danish authorities have estimated the number of electric vehicle could be around 600,000 by 2025. Since there are around 70 distribution companies in Denmark, the average number of electric vehicle for each distribution companies would accordingly be around 8600¹. Two charging rate scenarios are considered in the distribution networks (residential area) which include 2.3 kW (AC 10 A*230 V) and 3.7 kW (AC 16 A*230 V). Considering the worst case, i.e., the users simultaneously charging the electric vehicle, this will introduce loads of demand around 20 MW and 31 MW correspondingly to the distribution companies. Generally, the utilities have the capability to address this load growth.

However, as discussed in [36,52,77], congestion might happen in the middle or low voltage grid. Each distribution grid has a different history of development, such as in some cases congestion is first expected to emerge in the medium voltage grid, while in other grids the low voltage grid is considered to be more critical. In [36], the authors presented a case in the United States where the typical transformer serves anywhere from four to ten homes. In an area where the household load is 3 kilowatts (kW), the new load of an electric vehicle could easily double and become 6 kW per house. In areas where it is currently 6 kW per house, it could rise by 50 percent and become 9 kW per house (or more). In [77], a Danish case is presented to illustrate the changes of the load profile with one hundred percent penetration of EV and it is clearly shown that without any control, the transformer and the cable in a low voltage grid will be operated under pressure. As discussed in section 3.1.3, an electric vehicle owner in Denmark will probably charge the electric vehicle 20 times per month. Each time, the electric vehicle need to be charged five hours. Without any control, the distribution systems are operated with high load profile nearly fifty percent of a year.

Basically, the above discussion is an illustrative calculation on the load profiles of

¹It is noticed that Dong Energy Distribution is the largest distribution companies in Denmark, certainly the share of the number of electric vehicle will be high, this implies that other relatively smaller distribution companies share less comparing to the average numbers.

the distribution system. Some complicated models [78–81] have been proposed to address the load demand in distribution system considering the electric vehicle charging behavior and can give more accurate estimation on the impact of the EV loads to the distribution network.

4.1.2 Congestions management in distribution network operation and its enabling functions

Typically, the challenges in the distribution grid caused by demand spikes are solved by expanding the grid to fit the size and the patterns of demand. As an alternative, inspired by the congestion management at the transmission level ², described in section B.3. This study will consider allocation of the capacity of the distribution network according to economic principles. In order to identify and solve congestion problems caused by the increasing new loads such as electric vehicles, heat pumps, the distribution system operator requires additional information about the current and anticipated operating state of the distribution grids. This implies a need for measurement equipment and/or technology enabling identification and anticipation of load patterns and grid 'bottlenecks'. Key operations for DSO congestion management in a smart grid operation would be:

- Demand forecasting (conventional loads and new demands such as EV and heat pump)
- Generation forecasting
- Grid state estimation
- Online grid measurements
- Real-time intervention in case of unexpected deviations challenging grid reliability
- Meter data collection and analysis

However, DSOs' tasks in conventional system operation [82], are mostly focused on 'off-line' tasks related to asset management and maintenance during normal system conditions. The primary objective under emergency conditions is to organize restoration of the network as quickly as possible. Distribution systems

²The methods for congestion management in the transmission system is described in section B.3. In addition, the similarities and differences of congestion management in the transmission system and distribution networks are also compared in that section.

today tend to be weakly monitored as compared to transmission grids, and they are controlled in a decentralized fashion on the basis of pre-configured local controls (e.g. by means of grid codes and protection settings).

To illustrate a future operation scenario or smart grid operation scenario with a higher level of automation, in [83, 84], smart grid for distribution systems has been envisioned and the benefits and challenges of implementing the many different distribution automation functions are also presented. It is believed that the functions required in a smart grid operation can be extended with additional online and data intensive acquisition from the functions existing in the current distribution grid operations.

4.2 Background knowledge of the market based control solution

4.2.1 What is market based control?

Market based control [51, 85–87], is a paradigm for controlling complex systems with conflicting resources. It typically includes the features found in a market such as decentralized decision making and interacting agents. As discussed in [85], the “control” in a market based system emerges from the individual goals of the agents rather than having a goal imposed from above. Compared to centralized control, there is no need for any of the agents in a market based system to know all the parameters of the system in order for the overall system to function smoothly. Instead, in the market, with very little information, i.e., price, it is possible to facilitate allocation of resource. In fact, the market-based approach has been recommended to be used in the power distribution system, such as the discussion in joint research center European Forum ³ or in the research [88].

There are many mechanisms which can be used to find the clearing prices such as the general equilibrium market mechanism explained in the following section, the auction based approach and contract net protocols described in section B.4 which are not the focus in the present thesis. The general equilibrium market mechanism is mainly considered due to the following reasons:

- Considering the size of the market in the distribution system level ⁴, it is

³European commission Joint research centre, Scientific support to capacity markets and the integration of renewables, Brussels (BE) - 22/07/13

⁴Imagine that the highly possible actors in this market will be multiple DSOs, multiple

easier for the DSO to use the price to regulate the FO's energy consumptions.

- Considering the fact that DSOs can be seen as a monopoly inside its network, it is reasonable for the distribution system operator being a central price coordinator whose role is to coordinate the load behaviors of the commercial actors. The central price coordinator is supported by the general equilibrium market mechanisms.
- Comparing the general equilibrium market mechanisms and the double auction approach, one simple explanation is that the former uses price to penalize the power consumptions during the peak moments, while the latter regards price as an incentive to shift the power consumptions during peak time. If the size of the market is not flourishing, it is assumed that the former one will solve the grid congestion more efficiently. More discussion regarding the comparisons between the 'penalty scheme' and the 'compensation scheme' is presented in the discussion section of this chapter, i.e., section 4.4.
- The general equilibrium can be easily adopted for large scale of distributed energy resources, individual households supported by the recently developed powerful computational devices [89] and the idea is recently studied in [90] where home area network management system and distribution utility company exchange information on energy consumption and price.

4.2.2 General equilibrium market mechanisms

General equilibrium market mechanisms is a microeconomic market framework that has been recently been successfully adapted for and used in computational multi-agent systems in many application domains [86, 87, 91]. Some properties of general equilibrium such as Pareto efficiency, coalitional stability, existence, uniqueness under gross substitutes, and convergence have been discussed in [91]. It is pointed out that there are many algorithms which can be used to search for a general equilibrium, some centralized, and some decentralized. The most common decentralized algorithm for this purpose is the price tâtonnement process which is a steepest descent search method. The pseudo-code of the algorithm is presented in [91]. The distributed price tâtonnement algorithm is modified in the present thesis to facilitate the allocation of the grid capacity to the FOs. The algorithm can be mathematically supported by the combination of dual decomposition method and subgradient method which are described in

FOs or aggregators which means the number of the actors will be countable. Besides, note that the purpose of this market is to solve the grid congestion issue, which means for each DSO, they only interact with the FOs who use its network.

section B.5. In the process of find the equilibrium, the market participant, i.e., the fleet operator can choose different approaches to participate into the market, such as strident antagonist or cooperative antagonist, described in section B.6. It is assumed that the market participant will honestly behave in the market in the present study.

4.3 Main results

4.3.1 Map of the market based control operation

As we have explained in chapter 1, four functional levels are applied to address the congestion problems and have been adopted into four fundamental stages: 1, Offline planning. 2, Online scheduling. 3, Real time operation. 4, Offline settlement.

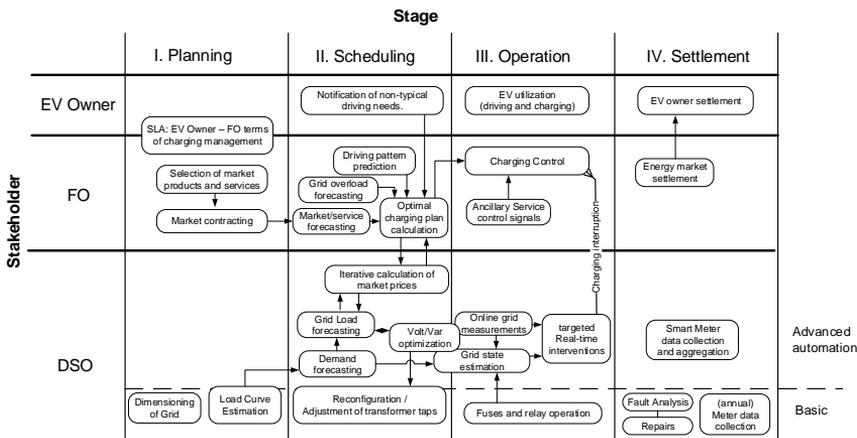


Figure 4.1: Map of distribution grid capacity market operation

In the first stage, planning has been distinguished from scheduling in the same fashion as unit commitment is distinguished from dispatch: depending on the specific coordination strategy, we distinguish operations that can be coordinated in a ad-hoc fashion and those that provide the basis for such ad-hoc decisions. The online scheduling stage can in time be closely coupled with operation (e.g.

reactive scheduling with a 5min resolution) or extend hours or days ahead of it. Scheduling is the stage in which available resources are best known and the platform for execution is to be prepared. The operation stage is about pure execution in real-time. Plans are only executed, and unplanned events occur and physical as well as automatic controls respond without deliberation. Settlement is about the aftermath: recordings (measurements, sent commands, etc.) of executed operations are consolidated and (financial) responsibility is allocated. Due to these clear distinctions, the four stages supports the discussion of interactions between key operation tasks for cross-stakeholder coordination for the complete process.

In the study, the operations DSO, FO and EV owner would be required to execute in the market based control scheme are mapped out which is shown in fig. 4.1. More explanations are found in paper A.5.

4.3.2 Market based approach for grid congestion prevention

We focus on stage 2, i.e., scheduling and the main results of developing the market based control for grid congestion prevention are presented in paper A.6. A cost and schedule adjustment algorithms modified from previous introduced distributed price tâtonnement algorithm is presented in the following. The purpose of the algorithm is to minimize the charging cost of EV fleet as well as preventing the grid congestions. The above algorithms describe the details of the market based control. For case studies and simulations, please refer to paper A.6.

4.3.3 Price coordinated hierarchical scheduling system

Based on the understanding obtained from the study in paper A.5 and A.6, the proposed scheme is further extended into a price coordinated hierarchical scheduling system in paper A.7. The extensions lie in the discussion of applying several approaches to find the price inside the market, such as uniform price auction mechanism and the general equilibrium market mechanisms. In addition, we also discuss the control relationship between the FOs and the EVs, such as instead of central scheduling and control of the charging profile of the EV fleet, the EV users can individually make the charging schedule given the price. The combination of applying market based control for the interaction between the DSO and the FOs and using the decentralized coordination between the FOs and the EVs is simulated and presented in paper A.9.

Algorithm 1 Cost and schedule adjustment algorithm

function 1. SCHEDULE GENERATION AND CONGESTION VERIFICATION

FOs calculate the optimal charging schedule and send the schedule to the DSO/market operator.

The DSO/market operator conducts congestion verification, if happens, go to function 2, otherwise, the energy schedule is approved.

end function

function 2. OPERATION OF MARKET BASED CONTROL

Initialize the shadow price which reflects the grid capacity margin.

loop

DSO/Market operator sends the price to all the FOs.

FOs updates the charging schedule and bid the charging schedule to the market operator.

The market operator updates the shadow price and broadcasts it to all the FOs, until the price converges.

end loop

end function

function 3. ADJUSTMENT

loop

The new shadow price is sent to FOs.

Go through function 1 and 2, until $\Lambda(i) \leq 0$, i.e., the shadow price is less than or equal to zero, then terminate the iteration.

end loop

Bid final energy/power schedule to the electricity spot market.

end function

In paper [A.9](#), we compare the results of two cases where the DSO both use the market based control to interact with the FOs, however, the coordination methods between the FOs and the EVs are different. In the first case, three fleet operators are assumed to centrally schedule and control the electric vehicle' charging which is also the scenario in paper [A.6](#), while in the second case, it is assumed that three fleet operators only aggregate the charging schedules which are made by the electric vehicle controllers. The results show that the congestion problems are solved after 5 steps in the first case while only 2 steps in the second case. The difference is because that the electric vehicles in the first case are always responding the shadow price and trying to avoid the charging on the higher price period, as a result, the electric vehicles will be scheduled to charge at other lower price period where congestion might happens as well. While in the second case, only some electric vehicles are assumed to responds to the shadow price which means that only part of the charging plan is rescheduled to other lower price period and thereby reduce the possibility of causing a new congestion period.

4.3.4 A flexibility clearinghouse concept (FLECH)

As aforementioned that this project is associated with the Danish iPower project, one of the highlights of the project is the concept of FLECH (a flexibility clearinghouse). In paper A.8, we presented the concept for facilitating ancillary services at the distribution system level. With the emergence of new players in distribution system ancillary service markets, it is foreseen that such a mechanism will be needed to minimize transaction costs. In contrast to other contributions on distribution congestion mitigation, the FLECH adapts to the actual DSO needs and is not tied to a specific aggregator architecture. The role of FLECH and its interactions with stakeholders of the distribution flexibility service market are illustrated in Fig. 4.2. Note that the single side auction mechanism is used by the FLECH to find the price, i.e., the equilibrium in the market.

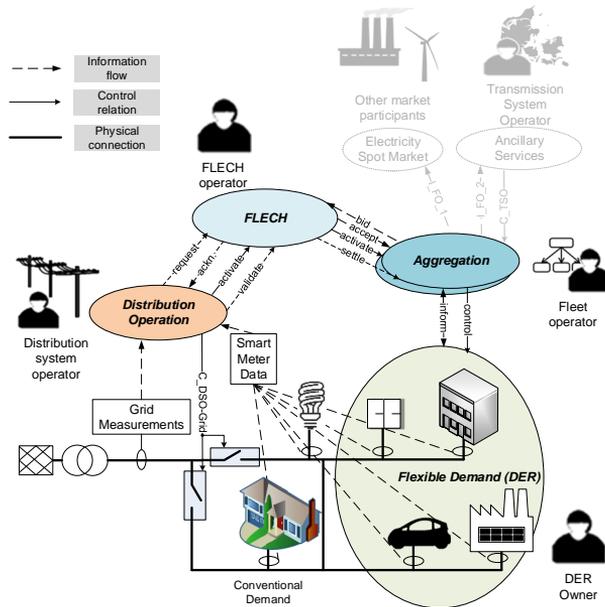


Figure 4.2: Schematic overview of the considered actors and their roles in relation to the FLECH

A case study has been presented showing how FLECH is envisioned to facilitate the service required by the DSO. In the scenario, distribution system operator foresees that a low voltage transformer will be overload by the power consumption of electric vehicles.

At the *planning* stage, the DSO submits the following service tender to FLECH:

PowerMax: Ensure that the capacity limits specified here are not violated:

CAPACITY REDUCTION [AREA T1]: 37.8kW

TIME 4:30pm TO 8:00pm ON weekdays

PERIOD 01 Dec 2014 TO 28 Feb 2015

RECOMMENDED RATE 10 EUR/kW

This tender is then announced by FLECH to all fleet operators registered for area T1. The fleet operators bid into the FLECH:

AggID [BidID]: reduction FROM capacity AT rate flex?

F01[F01B1]: 12.3kW FROM 14.8kW AT 10 EUR/kW FULL

F02[F02B1]: 12.3kW FROM 14.8kW AT 12 EUR/kW FULL

F02[F02B2]: 15.4kW FROM 18.5kW 20 EUR/kW FLEX

Note that FO1 did not bid with all of its resources, effectively only using 4 out of 5 cars, and that the second bid by FO2 is FLEX bid, i.e., it does not need to be accepted entirely. After gate closure their bids are forwarded to the DSO which evaluates the offers and decides to accept the following bids:

BidID: F01B1, F02B1, F02B2*90% AT 20 EUR/kW

This leads to an effective capacity reduction of 38.5kW which fulfills the required 37.8kW. The prices of this case study are completely fictitious and not anchored in real costs. We further use a multiagent system to demonstrate the case study, the developed multiagent system will be described in section 5.2.2 of Chapter 5.

4.4 Summary and discussions

4.4.1 Comparisons among the three control strategies

Although the centralized control and price control for distribution grid congestion management are not investigated directly, some comparisons can still be performed thanks to relevant topics studied in [9] and [8]. In both studies, grid congestion management and EV integration are investigated. In [9], day-ahead dynamic tariff control is used. In [8], centralized approach is utilized. In order to intuitively illustrate the interactions/control relationships between the involved actors, Fig. 4.3 shows information flows of the market based control, price control and centralized control for distribution grid congestion prevention. We adapt and draw the information flows presented in [9] and [8] into the current one.

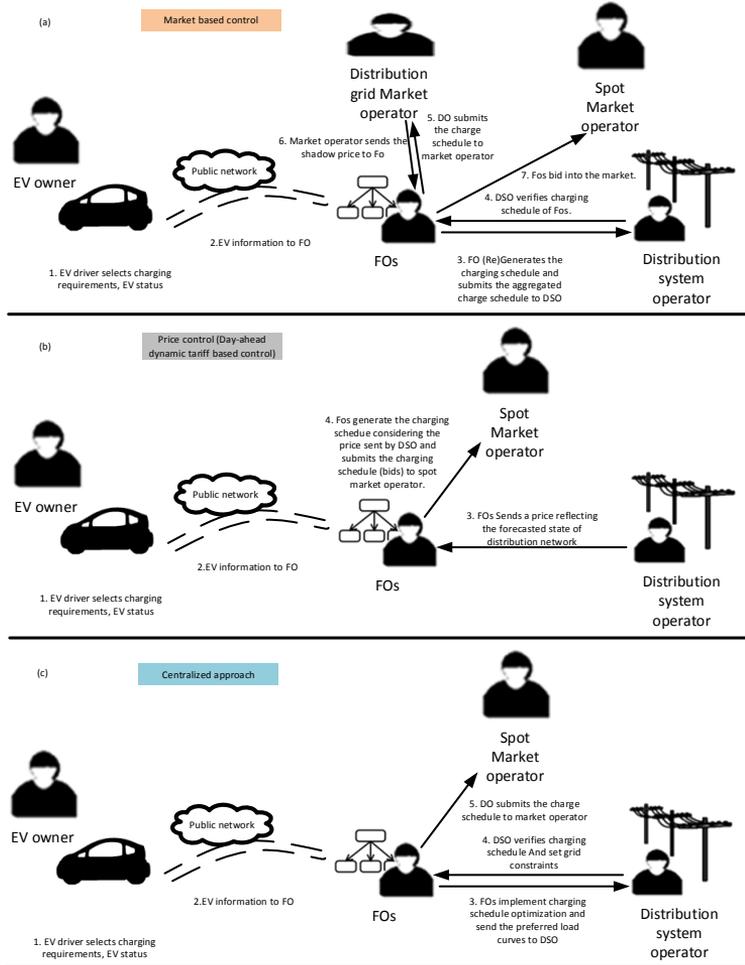


Figure 4.3: Information flow of the three control strategies for distribution grid congestion prevention

From figure 4.3, it is shown that EV owners firstly communicate with the FO to define their personal requirements in all three studies [8, 9] and paper A.6. Then, the FOs make the charging schedules for the electric vehicles. In the case of price control, the FOs may be firstly notified by the DSO with a price signal reflecting the forecasted congestions, then the FOs generate the charging schedule considering the price sent by the DSO and submit bids to the spot

market. This is different with the market based control and centralized control method where the FOs need to coordinate with the distribution grid market operator and DSO to prevent the congestions. The interactions between the FO and the DSO/market operator may require multiple iterations. Note that in the centralized control, the FOs will get an constraint (power limits) from the DSO every iteration, it is not addressed in [8] that how the constraint is set for each FO if multiple FOs share one power distribution network. In the market based control, this is handled by the economic principles, and the negotiation is facilitated by a market operator. It should be pointed out the market operator could be an independent entity such as the case in A.8 or be the same entity with the DSO such as the case in paper A.6.

Some comparisons are listed in Table 4.1, which is shown in the following.

Table 4.1: Comparison of control strategies for distribution grid congestion management

Actor	Complexity	Value	Risk	Other issues
Market based control				
<i>FO</i>	High	High	Low	Privacy improved, flexible, price and technical constraint are resolved via the general equilibrium market mechanism.
<i>DSO</i>	Relatively high	High	Low	Enable a comparatively high utilization factor of the grid.
Price control				
<i>FO</i>	Medium	Low	Low	Easy to interact, price received.
<i>DSO</i>	Medium	Medium	High	N.A.
Centralized control				
<i>FO</i>	Medium	Low	Low	Easy to interact, technical constraint received.
<i>DSO</i>	Medium	Medium	Low	N.A.

The overall rationale is to provide cost-efficient solutions, no firm quantification of benefits or costs have been performed in the thesis. In addition to this, this thesis has not addressed one aspect of distribution grid congestion management, i.e., the long-term problem of distribution grid reinforcement-deciding when and where to build new transmission facilities. Such discussions can also be found in [43,52] where the importance is emphasized and some illustrative calculations are presented. However, it is clearly stated in [43,52] that smart control strategies incurred demand response is most likely the attractive way for the DSO to solve the congestion if it only occurs a few times per year. Besides, regarding the discussion on pricing through compensation mechanism or through penalty

mechanism, if we use a dialectic perspective to view the two mechanisms, there is no big differences. For example, the cost saved by the DSO on new investment could be used for compensation in the congestion market or in another way, the saving could be directly share with all the customers firstly, then, the DSO can use the price to penalize the one who use the electricity in the peak time.

4.4.2 Market based control related issue

The overall assumption for market based control is that there exists an equilibrium price that will clear the negotiation in each round, e.g., the negotiation between the market operator and the fleet operators. This works fine when the cost functions of the fleet operators are convex. However, the presence of units cost functions that are not strictly convex which brings some difficulties in finding the clearing price. In a traditional auction-based market, like Elspot or the regulating power market when the price is determined by submitted bids, this problem can be overcome by only accepting the bids needed. However, in the present case, the market operation method is different. In the present case, one situation might happen, i.e., that the fleet operators respond the same way if the given price range is not obvious which means that the iteration numbers may increase a lot to find the clearing price. Some studies [90, 92, 93] have been given on solving this problems. In [90, 93] the suggestion is using primal averaging method if the objective function of the market participant is neither strictly convex nor finite and the authors in [93] proved that the algorithm (dual decomposition and sub-gradient method which supports the price finding in the general equilibrium market) finds near-optimal schedules even when advanced metering infrastructures (AMI) messages (updated prices and residential load) are lost, which can happen in the present communications network. In [92], a method using randomized price offsets was presented to deal with non-convex, non-continuous supply and demand functions. The method relied solely on small but fair alternations of the price signal for each prosumer leaving the utility functions untouched and the results showed that both the convergence behavior and solution quality improves with the market size

Besides, although using market based approach has been demonstrated to enable an optimal resource allocation, the uncertain in terms clear business models for fleet operators and distribution system operators, and the necessity for the regulatory support makes using price as a coordination tool for serving grid services is still a challenging task. But, some lessons can be drawn from the present study, if the size of the market is great, an independent capacity market could be created to facilitate the transactions between distribution system operators and fleet operators, maybe in a national level. However, if the size of the market is small, the market based control could be facilitated by a functions insides the

distribution system operation. Nevertheless, to ensure enough competition and fairness of the capacity market, one prerequisite is the number of market participants, i.e., fleet operators. If there are few fleet operators in the distribution area, issue e.g., market power will become a major challenge from the market perspective. A mechanism needed to be developed to hedge the risks.

Multi-agent system for distribution grid congestion management

In this chapter the main results regarding the third research objective are summarized. The main results have been mainly presented in the manuscript [A.9](#) and [A.10](#), included in appendices of this report. The chapter starts with a general discussion on using multi-agent system (MAS) for a hierarchical organization based distribution systems. Then, the main finding of the third research topic are summarized.

5.1 Characteristics of multi-agents system

Jennings and Bussmann [94] pointed out that modern control systems must meet increasingly demanding requirements stemming from the need to cope with significant degrees of uncertainty, as well as with more dynamic environments, and to provide greater flexibility. This, in turn, means that control systems software is highly complex in that it invariably has a large number of interacting parts. It is argued in the article that analyzing, designing, and implementing such complex software systems could be implemented as a collection of interacting, autonomous, flexible components (i.e., agents) which affords software engineers several significant advantages over contemporary methods. The study firstly discussed that a canonical view of a complex system can be defined as the following in Fig. [5.1](#). The system's hierarchical nature is expressed through

the “related to” links; components within a subsystem are connected through “frequent interaction links”, and interactions between components are expressed through “infrequent interaction” links. The complex system specifically in the article is complex software systems (of which control systems is an instance).

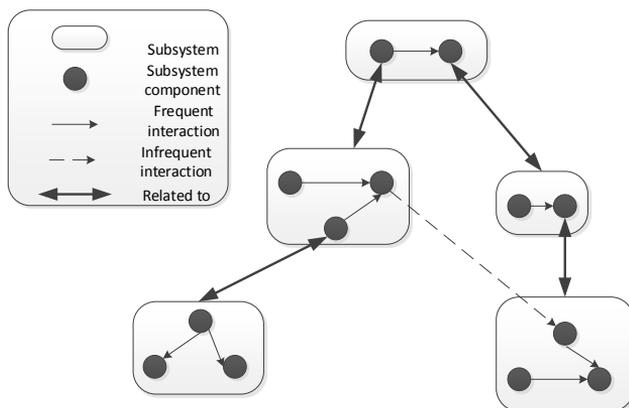


Figure 5.1: View of a complex system

It is further discussed that software engineers have devised several fundamental tools to help manage this complexity including decomposition, abstraction and organization approaches. Then the authors [94] argued that the case for agent oriented software engineering. The arguments are mainly performed from three aspects: 1) The merits of agent-oriented decompositions. 2) The suitability of agent-oriented abstractions. 3) The need for flexible management of changing organizational structures. In the article, a canonical view of an agent-based system (Fig. 5.2) is presented. Fig. 5.2 shows that: 1) adopting an agent-oriented approach to software engineering means decomposing the problem into multiple autonomous components that can act and interact in flexible ways to achieve their set objectives; 2) the key abstraction models that define the agent-oriented concepts are agents, interactions, and organizations; and 3) explicit structures and mechanisms are often used to describe and manage the complex and changing web of organizational relationships that exist between the agents. Regarding organizational relationships, the author in [95] show that four organizations are widely used for computer-based agents. Organization means a set of policies (rules and criteria) by which agents are aggregated to form greater or super-agents, just as birds, fish and people aggregate to form flocks, schools and corporations. In the study, it is discussed that a data flow and a control flow describe the structure of a super agent. Furthermore, the data flow is partitioned into two fuzzy subsets: the subset of strongly cyclic data flows, and its

complement; the control flow is partitioned into two fuzzy subsets: the subset of hierarchical control flows and its complement. Then, the super-agent can be partitioned into four regions, i.e., cyclic data, hierarchical control; cyclic data, null control; acyclic data, hierarchical control; acyclic data, null control.

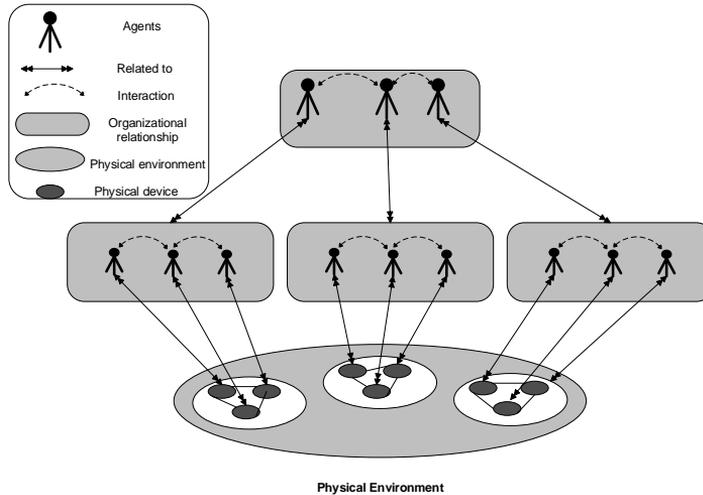


Figure 5.2: Canonical view of an agent-based system interacting with a physical environment

When adopting an agent-oriented view of the system, it is apparent that the agents will need to interact with one another, either to achieve their individual objectives or to manage the dependencies in the common environment. These interactions can vary from simple semantic interoperation (information passing), through traditional client-server-type interactions, to rich social interactions (the ability to cooperate, coordinate, and negotiate about a course of action). FIPA (The Foundation for Intelligent Physical Agents) standards¹ define a framework for inter-agent interaction in multi-agents system, it also specifies abstract architectures for multi-agents system implementation, as shown in Figure. 5.3.

Besides the application of agents, the FIPA architecture includes several services. A Directory Facilitator provides yellow page services i.e., different agents interact with this service to register and discover available agent services. Agent Management Services provide white page services. This agent is responsible for creating, destroying and managing agents and containers in a multi-agent plat-

¹FIPA, The Foundation for Intelligent Physical Agents:<http://www.fipa.org/>

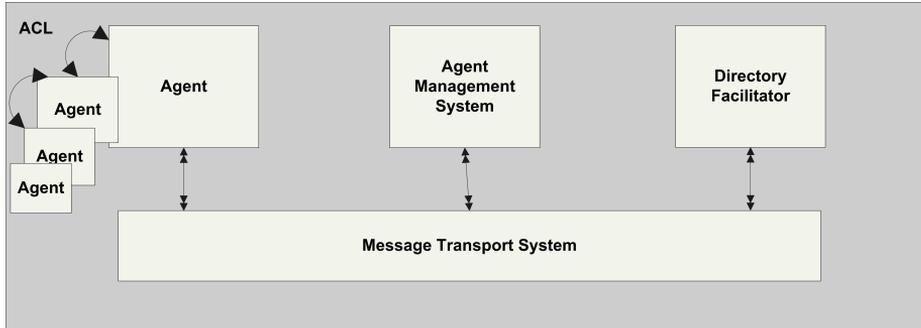


Figure 5.3: FIPA abstract architecture for MAS implementation

form. The Message Transport Service is responsible for message transportation between agents. This service also enables synchronization of messages when several messages are sent and received from different agents in parallel. FIPA also provides a language specification for communication between agents. This language specification is called the FIPA agent communication language (FIPA ACL).

5.2 Main results

5.2.1 Modeling the price coordinated hierarchical scheduling system by multi-agent concepts

In previous chapter, a price coordinated hierarchical scheduling system is proposed to optimally integrate electric vehicles into the distribution network where the DSO uses market based control to allocate the grid capacity among the FOs, and the control policies between the FO and the EVs are implemented both centrally and distributed. To simulate and evaluate the proposed scheme, a multi-agent system based technology is very suitable for modeling the proposed control systems. This can be justified by the following reasons:

- The increase in complexity and size of the whole electric vehicle charging network bring up the need for distributed intelligence and local solution, which fall into the scope of MAS based technology.
- The information flow, optimizations and the negotiations in the smart charging network of electric vehicles can be well demonstrated and inte-

grated into a MAS.

- The system can be pre-tested and pre-analyzed by using a MAS before going to real implementation.
- The MAS can be used to test different control strategies, various business scenarios, and different behaviors of the market participants.

An agent view of the price coordinated hierarchical scheduling system is presented in Fig. 5.4. In the figure, operations of the agents are not shown, nevertheless, it is shown that multi-agent based technology can be used to characterize a complex hierarchical system for scheduling.

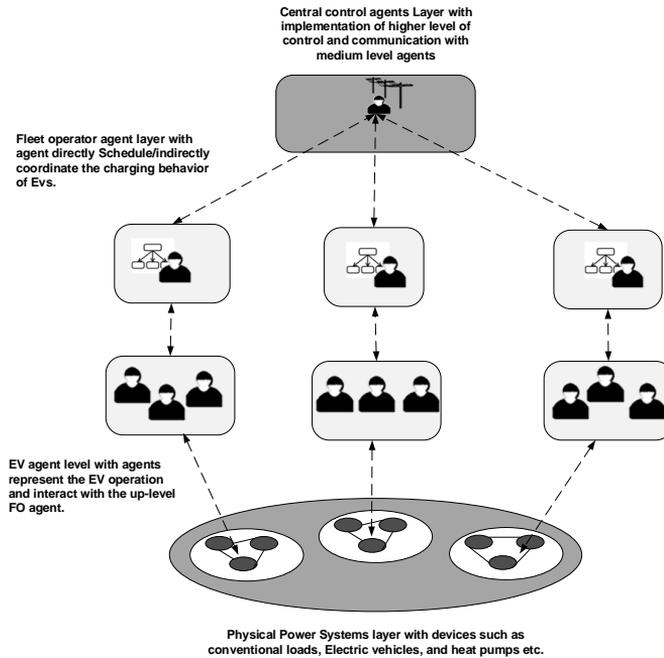


Figure 5.4: Agents view of the price coordinated hierarchical scheduling system

5.2.2 Platforms Development

To implement the multiagent systems described above, Fig. 5.5 illustrates the MAS system architecture, in which, all the agents are built in JACK which is

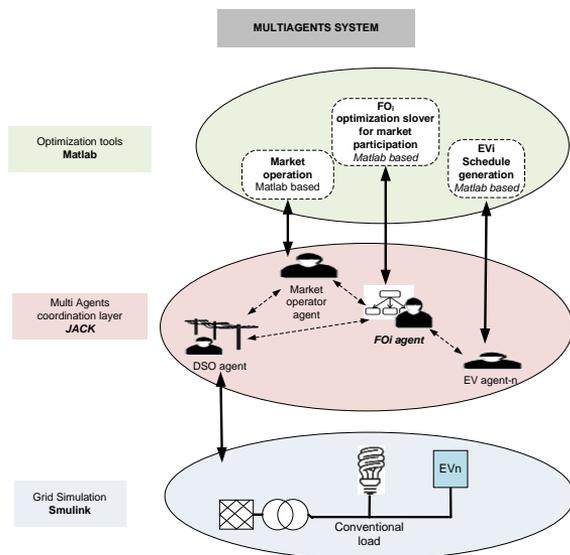


Figure 5.5: A MultiAgent system architecture.

an agent-oriented development environment built on top of and fully integrated with the Java programming language [96]. JACK offers the environment and facilities for message sending/receiving. MATLAB based functions enables a procedural implementation of decision modules. Simulink is used to model the distribution grid and for power flow calculation. The java application programming interface `matlabcontrol`² is used for JACK to interact with MATLAB. DSO agent interacts with the Simulink through a matlab file. A case study is performed to examine the developed platform. In the case study, one DSO agent, one market operator agent, three FO agents, and fourteen EVs agents are included. The simulations show that it well emulates the negotiation behavior inside a capacity market by the interaction diagrams. For more details such as the features of JACK, how the market actors in the system are mapped into the agents in the multiagent systems, and the simulation results, the readers are referred to manuscript A.9.

The platform has also been used to simulate a negotiation bidding framework in [97]. The negotiation sequence in [97] following the discussions in paper A.8 where three different agents, the DSO, the FLECH and the Fleet operator agent aim to eliminate the grid congestions by market based approach. The negotiation sequence shall find a price, i.e., the equilibrium for the market ne-

²<https://code.google.com/p/matlabcontrol/>

gotiation when services are initiated by the DSO. The framework is focusing on the day-ahead market and is using an auctioning approach to clear the market. It is assumed that this clearing does not necessarily happens in first bidding round, but could extend to several bidding rounds before the market clearance is found, although a max of 7 rounds is implemented. Several case studies have been tested to show the functionality of the negotiation platform including a simple case clearing in first round, two cases need multiple rounds where price and power are regulated to find the equilibrium, and a extreme case where the price is too high to find the equilibrium. The case studies illustrate that the platform is able to conduct negotiations which lowers the fleet operators' consumption in a certain period in exchange of an economic compensation to the fleet operators.

In addition, it is planned in paper A.10 that the platform will be used to explore a case study where the fleet operators have slightly more complex operations. In the study, the multiple fleet operators will do the similar negotiations with the distribution system operator as the one shown in paper A.9, but the fleet operators in paper A.10 will try to explore more economical benefits which can be offered by the electric vehicles. These extra economical benefits will be achieved by using the EV's discharging capability. The question is formulated as a mixed-integer non-linear programming based problem, implemented in General Algebraic Modeling System (GAMS) ³ using the DICOP Solver ⁴.

5.3 Summary and discussions

In this study, we developed and used an integrated environment consisting of JACK agent software and MATLAB/Simulink to analyze the interactions between the agents considering their own decision making, information flow exchanges and the influences on the physical grids. JACK is good for demonstrating the coordination schemes among the actors, MATLAB is competent to carry out the technical computation of optimization problem, Simulink is known for its interaction with MATLAB and it is adequate to perform the technical validation for the present study. In a general case, various simulation platforms can be utilized in a distribution grid congestion demonstration. For example, besides JACK, JADE ⁵ is also widely used for multiagent simulation. JACK is chosen because of its capability and support for the explicit modelling of the typical MAS entities such as agent, plan, event and capabilities. Moreover, in JACK it is easier to design and analyze interactions and dependencies among

³<http://www.gams.com/dd/docs/bigdocs/GAMSUsersGuide.pdf>

⁴<http://www.gams.com/dd/docs/solvers/dicopt.pdf>

⁵<http://jade.tilab.com/>

such entities. In term of solving an optimization problem, GAMS (the General Algebraic Modeling System) ⁶ also has good performance, however, MATLAB is easier to be used and seems more popular in the academically field. Last but not least, grid modeling tool is also an important part. The currently existing grid modeling tools include Simulink, MatPower ⁷, PowerFactory ⁸, ARISTO ⁹, NEPLAN ¹⁰ etc. However, here it is not the aim to give a comparison of the various platforms, instead, we want to emphasize that the relevant tools can be integrated with the MAS settings.

Currently, the agents in this project can be categorized as being reactive because the agents chooses their actions based solely on the immediate input and some logical control defined for the study. In order to fully use the advantages of different simulation tools, especially if the multi-agent system is used for real time control simulation, a simulation methodology such as using high-level architecture that allows individual subsystems/components to be simulated by different simulation tools running simultaneously and exchanging information in a collaborative manner need to be implemented. This could be a topic for future work.

⁶<http://www.gams.com/>

⁷<http://www.pserc.cornell.edu//matpower/>

⁸<http://www.digsilent.de/index.php/products-powerfactory.html>

⁹Advanced Real-Time Interactive Simulator for Training and Operation, Sweden

¹⁰<http://www.neplan.ch/>

Conclusions and Future Work

This thesis firstly examined three control strategies for the exploitation of service based electric vehicle aggregation, mainly from a commercial actor's perspective. Then, the thesis investigated the control strategies for the distribution system operator to coordinate with the commercial actors to eliminate grid congestion. Finally, to evaluate the proposed control strategies, a multi-agent system is used to model and simulate the system. The main outcome of this project is a price coordinated hierarchical scheduling system for large scale integration of electric vehicles into the power distribution network. In this system, the distribution system operator uses market based control to interact with the commercial actor to prevent the grid congestions. The commercial actor uses either direct control or price control to manage the distributed charging behavior of electric vehicles depending on the actual situations. This chapter presents a number of key results from the present study and recommends several topics for future work.

6.1 Conclusions

In section 1.2.2, three research problems are outlined for the project. In the following, the results are concluded:

1. For a commercial actor (fleet operator in the present thesis), how to choose a control strategy to manage a large scale of electric vehicles?

Based on the review and methods development presented in chapter 3, centralized direct control and price control are concluded to be more suitable

comparing to market based control for management of a EV fleet. Centralized direct control offers the best performance in controlling the EV fleet and therefore making better optimized charging profiles, especially if the participation into the regulating power markets was considered. For the centralized direct control, it is recommended that linear programming based techniques is considered to characterize the optimal charging problem and generate the optimal charging schedule. In order to generate an optimal charging schedule, a forecasted electricity price and predicted EVs driving pattern are essential. Fortunately, they can be estimated by the commercial actors. Nevertheless, EV owners are encouraged to submit a provisional EV utilization plan for next day to the commercial actor for generating an optimal charging schedule. For the centralized control to become a success, more research is needed in setting up a collaborative business model which ensures the proper engagement of commercial actors and EV owners.

Price control is probably the most attractive way for the commercial actor to regulate the charging behavior of the electric vehicles considering its easier implementation. It is especially effective in the case of decreasing the charging in the peak time for DSO or the case of increasing the load for transmission system operator¹. For the price control to become a success, more research is needed in price responsive models or price elasticity models to obtain satisfactory performance and grid reliability. Market based control is not recommended here considering some barriers, such as an automated negotiation device need to be mounted in the electric vehicle which performs the enabling function if using the market based control. Such automated control devices are not currently available.

2. To manage the congestion of the distribution network, which control strategy should be considered taking into account the distribution system operator, the commercial actor's self-interests and operational constraints?

The thesis focused on the development of control strategies for the DSO to interact with the commercial actors instead of distributed demand side units such as individual EVs, heat pumps etc. Three control strategies have been examined and compared in section 4.4.1. The chosen market based control is being developed and tested. There are several advantages for the utilization of market based control. First, market based control is proven to be an effective way of allocating conflicting resources. Second, the negotiations required in the market can be enabled and operated by the DSO and commercial actors without much burden. Third, market

¹Using price control for providing services to transmission system operator is not the focus of this thesis, for such discussion, please refer to Ecogrid EU project <http://www.ecogrid.net/>. In addition to this, in [98], the authors prioritizes the needs to handle the conflicting resources, e.g., the services required by the transmission system operator might cause overloading issue for distribution network.

based control can ensure a low risk for DSO when solving the grid congestion, since price and power schedule are resolved via the price clearing mechanisms. In section 4.2.2, general equilibrium market mechanisms are used to find the clearing price instead of auction approach. In order to benefit from the market based control strategy, more work is needed for studying the non-convex cost problem which has not been addressed in this thesis.

3. Development of tools to simulate the control strategies developed for distribution grid congestion management.

It is demonstrated that multi-agent system based technology is very suitable to evaluate the development of market based control strategies considering the DSO and FO's operations. Motivations have been given in section 5.2.1, in addition, for a practical case using the market based control scheme, the market participant may behave differently, which can also be well simulated in a multi-agent system.

6.2 Future Work

The present research addressed a comparatively open and new field of study and there is a large scope for continuing the current work. Some topics are listed below to direct future research as a follow-up to this project.

- Commercial actors, having integrated control strategies such as direct control and price control may be a feasible solution to mitigate the downside of the price control. In addition, considering the fact that maybe some customers prefer their EVs directly controlled while some EV users would like to receive the price signals and respond the price individually, it is interesting to make a study to analyze the related issues. A preliminary study [99] has been performed where the modern portfolio theory was adopted.
- Similarly, the distribution system operator, having an integrated control scheme such as direct control, market based control and price control may be a feasible solution to mitigate the uncertainty of the price control, the high communication cost of market based control and the high computational cost of direct control. It is interesting to e.g., design a framework for choosing the suitable control strategies such as one that is based on the available controllable resources, the control requirements, and the relevant information and communication facilities.

- The overall rationale of the present work is to provide cost-efficient solutions, but no quantification of benefits or costs has been performed. Future analyses could be performed on the cost of the different control concepts. For example, for an advanced control concept, the immediate benefits may appear less obvious, compared with the complexity that is introduced to realize it. In addition, the long-term marginal costs of reinforcement of the grid could also be performed in order to be able to compare these costs with the cost involved to make the end-users reducing demand in a given period to avoid congestions in the distribution grid.
- In order to fully understand the grid congestion problem, a distribution grid power flow calculation method should be chosen and used to support the control strategy. For example, the network flow model and Newton-Raphson method have been used in [8] where centralized control is used to prevent the grid congestion; the optimal power flow based calculation is used in [9] where day-ahead dynamic price control is used to manage the grid congestion. To fully integrate the market based control with the power flow calculations, the recently proposed alternating direction method of multipliers (ADMM) could be used to facilitate the integration. This idea is currently under investigation, please see the further discussion in section B.7.
- Mainly, thermal limits of the distribution grid has been investigated in the present work, but it is also known that other constraints such as voltage limits are important and need to be studied. In a practical way, in the planning period, the DSO considers and pre-handles voltage problem by reinforcing the grid infrastructure based on the regulations. These regulations describe the allowed voltage safety limits in the distribution grid. In the normal operation period, on the substation level, transformers has tap changers which can be used to regulate the voltage. In Denmark, in general, 60kV/10kV transformer has on-load tap-changers. In the future, the system operator could set up grid codes for DERs, requiring the DERs to have their own embedded voltage control, which could solve the problem preventively. In the context of this study, voltage control can also be implemented by e.g., market based control scheme which could be an interesting topic for future work.

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APPENDIX A

Core publications

A.1 Optimization and control methods for smart charging of electric vehicles facilitated by fleet operator: review and classification

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OPTIMIZATION AND CONTROL METHODS FOR SMART CHARGING OF ELECTRIC VEHICLES FACILITATED BY FLEET OPERATOR: REVIEW AND CLASSIFICATION

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ABSTRACT

Electric vehicles (EV) can become integral parts of a smart grid, since they are capable of providing valuable services to power systems other than just consuming power. As an important solution to balance the intermittent renewable energy resources, such as wind power and PVs, EVs can absorb the energy during the period of high electricity penetration and feed the electricity back into the grid when the demand is high or in situations of insufficient electricity generation. However, the extra loads created by increasing EVs may have adverse impacts on grid. These factors will bring new challenges to the utility system operator; accordingly, smart charging of EVs is needed. This paper presents a review and classification of methods for smart charging of EVs found in the literature. The study is mainly executed from the control theory perspectives. Firstly, service dependent aggregation and the facilitator EV fleet operator are introduced. Secondly, control architectures and their integrations in term of electricity market and distribution grid are discussed. Then, data analysis of EVs including a battery model and driving pattern is presented. Further discussion is given on mathematical modelling and control of smart charging of EVs. Finally, the paper discusses and proposes future research directions in the area.

1 INTRODUCTION

EVs are commonly recognized as smart grid assets in addition to their primary transport function. They can be utilized to balance power fluctuations caused by the high penetration of intermittent renewable energy sources [1], [2]. However, a large scale application of EVs also mean new loads to electric utilities, and undesirable peaks may exist in the distribution network when recharging the battery [2]. All these factors bring new challenges to the system operator. As a result, smart charging (including power to vehicle and vehicle to grid (V2G)) solutions are needed which can make EV an asset to the grid rather than a mere traditional load and make the grid more flexible.

Much research has been done to address the above challenges. The purpose of this study is to give a review and classification of the control strategies used for smart charging of EV fleets. From the literature, it is summarized and concluded that a new business entity, namely the EV fleet operator (FO) has been widely proposed capturing the new business opportunities by providing the multiple services of EVs and then by this contributing to the challenges solving of power distribution system operator. Alternatively names for an EV FO are used such as EV virtual power plant, EV aggregator, EV charging service provider or EV service provider (EVSP). The new entities [3], [4] could be independent or integrated in an existing business function of the energy supplier or distribution system operator.

In principle, two types of control architectures are used by FOs when aiming at the above objectives, named centralized and decentralized control. Centralized control means electric vehicles can be aggregated and controlled by FO directly, while the decentralized control usually is implemented in the form of price signal, i.e. the individual EV optimizes the charging based on the electricity price information made available to them either from EV FO or the utility. A comprehensive discussion and comparison on these architectures can be found in [5], [6]. From the discussions in [5]-[7], it can be shortly summarized that for a centralized charging the decisions are made on the system-level and therefore can give better results such as ensuring the safety of the distribution network; however, the cost of communication infrastructure would be high for centralized charging. For a decentralized charging, one of main advantages is the possibility to minimize the communications infrastructure cost [8], however, the solution may or may not be optimal, depending on the information sharing and methods used to make the charging scheme.

The paper is organized as follows: The control objectives are discussed in Section 2. Section 3, 4 describes the role and control architectures of EV FO. The battery model and driving patterns of EVs are briefly discussed in section 5. Some commonly used algorithms in the centralized and decentralized control of smart charging of EVs are presented in Section 6 and 7, respectively. Section 8 concludes the paper with some suggestions for future research.

2 SERVICE DEPENDENT AGGREGATION

In [9], Lopes et al. shortly summarized that a large deployment of EVs will involve the following studies: 1) Evaluation of the impacts that battery charging may have on system operation; 2) Identification of adequate operational management and control strategies regarding batteries' charging periods; 3) Identification of the best strategies to be adopted in order to use preferentially renewable energy sources (RES) to charge EVs; 4) Assessment of the EV potential to participate in the provision of power system services, including reserves provision and power delivery, within a vehicle to grid (V2G) concept. Inspired by this summary, we will first review four kinds of goals when investigating in smart charging of an EV fleet. In addition, we also see these four objectives as four types of opportunities and products that can be captured by FOs and then provided to other actors in a smart grid context.

2.1 Providing ancillary services to the transmission system operator (TSO)

Kempton et al. [10], [11] analysed the potential profits of V2G support by comparing it to existing ancillary services and found that participating regulation power market appears to be most promising and offers a substantial earning potential to EV owners. Roterig and Ilic [12] took into account vehicle to grid as a mean of generating additional profits by participating in the ancillary service markets. Based on the data of the independent system operator of California, provision of regulating power substantially improves plug-in hybrid electric vehicle economics and the daily profits amount to \$ 1.71, including the cost of driving. Han et al. [13] proposed an FO that manages EVs to provide frequency regulation services, the cost arising from the battery charging and the revenue obtained during the participation is investigated. The problem is formulated as an optimization problem and dynamic programming is used to generate the charging control profile. Divya et al. [14] carried out a study investigating the feasibility of integrating EVs in the Danish electricity network which is characterized by high wind power penetration. They found that EVs have the potential to assist in integrating more wind power in 2025 when the EV penetration levels would be significant enough to have an impact on the power systems. Tuffner and Meyer [15] explored two different charging schemes: V2G Half and V2G Full to handle the entire additional energy imbalance imposed by adding 10GW of additional wind to the Northwest Power Pool. The result indicates that the proposed frequency based charging strategy can meet the new balancing requirements. However, this also depends on the charging station availability (residential and public charging station), the economics of the implementation and a viable and compelling business model. All these results indicate that it is reasonable and profitable to participate in the electricity market and provide ancillary service to the grid.

2.2 Providing services to renewable energy source (RES) supplier

Lopes et al. [16] investigated the dynamic behaviour of an isolated distribution grid when wind power and electric vehicles are presented. The objective is to quantify

the amount of intermittent RES that can be safely integrated into the electric power system with the utilization of EVs' storage capacity. Another study [17] by the same author analyse two tasks. The first part of the work studied the maximum share of EVs on the low voltage networks without violating the system's technical restrictions. The second part focused on the prevention of wasting renewable energy surplus when charging the EVs. The results indicate that the grid can allocate higher penetration of EVs with a smart charging strategy compared with a dumb charging and that the EVs have the capability to store energy and discharge to grid later into the system. In this way, the RES can be utilized more. Lund and Kempton [18] investigated the impact of using V2G technology to integrate the sustainable energy system. Two national energy systems are modelled; one for Denmark including combined heat and power (CHP), the other is a similarly sized country without CHP. The model (EnergyPLAN) integrates energy for electricity, transport and heat, includes hourly fluctuations in human needs and the environment (wind resource and weather-driven need for heat) The results indicated that adding EVs and V2G to these national energy systems allows integration of much higher levels of wind electricity without excess electric production, and also greatly reduces national CO₂ emissions.

2.3 Minimizing charging cost

An electricity market is presumed and is ideally suited for the application of optimal charging control; this is because the various hourly market prices can bring benefits for EVs if they are scheduled to charge in the period of lower prices. Within this scope, most the work [19]-[21] assume that the EV FO manages the electricity market participation of an EV fleet and presents a framework for optimal charging or discharging of the EVs. In addition, the electricity price of the day-ahead spot market and the regulation market and the driving patterns of the EV fleet are usually assumed to be known by the FO who is assumed to be the price-taker in the electricity market in studies. However, Kristoffersen et al. [22] also investigated the possibilities of EV management where the FO has a significant market share and can affect electricity prices by changing the load through charging and discharging. Besides studying the optimal charging from an EV fleet perspective, research in [12], [23] showed how dynamic programming can be utilized by the individual EV controller to make an optimal charging schedule taking into account the electricity market price. In [24], an intelligent charging method is proposed which responds to TOU price and minimize the charging cost.

2.4 Providing ancillary services to distribution system operator (DSO)

It is assumed that the distribution network has the capacity to allocate new loads when achieving the objectives discussed above. With the objective of avoiding grid bottlenecks, the purpose of the smart charging is to solve the potential grid congestion problem. Many investigations has been performed studying the impact of EVs on grid, which can be dated back to the early 1980s [25]. In [26], the authors gave a review and outlook about the impact of EVs on distribution networks. Sundstrom

and Binding [27] considered the power grid on the Danish island of Bornholm, where the grid of the isolated island is used to study the impact of EVs and the potential profit to be made of grid services. The focus of the paper is on proposing a method for planning the individual charging schedules of a large EV fleet as well as respecting the constraints in the low-voltage distribution grid. The impact of EVs on the electricity grid is studied in [28], where the focus is on the Vermont power grid. They assume a dual-tariff, nightly charging scheme, and conclude that enough transport capacity is available in the power grid. Lopes et al. [29] studied the potential impact on a low-voltage distribution grid. Smart charging behaviour is here considered to maximize the density of EV deployment into the grid, i.e., to reach the maximally tolerable number of EVs and meanwhile maintaining grid constraints. Kristien et al. [30] investigated the impact of charging EVs on a residential distribution grid and illustrated the results of coordinated and uncoordinated charging. Without coordination of the charging, the power consumption on a local scale can lead to grid problems. While the coordination of the charging can reduce the power losses, power quality is improved to a level which is similar to the case where no EVs are present.

2.5 Analysis of the research framework and the goals of smart charging

Several questions would naturally arise after reviewing the four goals described in 2.1 to 2.4, e.g., whether some goals can be integrated when making the optimal charging schedules of an EV fleet, what are the relationships between these four goals. In [12], the authors took into account vehicle to grid as a mean of generating additional profits by participating in the ancillary service markets and integrated it with the goal of minimizing the charging cost of the EV. The result indicated that the combined goals substantially improve EV economics. Sundstorm and Binding [27] considered the distribution grid congestion issue when minimizing the charging cost of an EV fleet. It is observed that multi-goals study is already performed, however, a systematic way of understanding the relationships between the described goals is missing.

In general, relationships between goals can be described as [31]:

- Independence: the goals do not affect each other.
- Cooperation: achieving one goal makes it easier to achieve the other.
- Competition: one goal can be achieved only at the expense of the other.
- Interference/Coordination: one goal must be achieved in a way that takes the other goal into account.

We use these four relationships as guideline and analyse the relationships between the four goals of smart charging. Table 1 presents the results.

Table 1: Relationships between the four goals discussed above

	<i>Providing services to RES supplier</i>	<i>Providing ancillary services to TSO</i>	<i>Minimizing charging cost</i>	<i>Providing ancillary services to DSO</i>
<i>Providing services to RES supplier</i>	N.A.	Cooperation	Cooperation	Coordination
<i>Providing ancillary services to TSO</i>	Cooperation	N.A.	Cooperation	Coordination
<i>Minimizing charging cost</i>	Cooperation	Cooperation	N.A.	Coordination
<i>Providing ancillary services to DSO</i>	Coordination	Coordination	Coordination	N.A.

It is shown in Table 1 that the first three goals needed to be coordinated with the last one, and this coordination is usually called congestion management in distribution network and the topic has recently attracted many researches. Besides, Table 1 shows that the first three objectives can be well integrated when generating the optimal schedule of EV fleets. With this qualitative analysis, it is beneficial for the FO to make global optimal schedules.

3 INTRODUCTION OF FO IN THE CONTEXT OF SMART GRIDS

From previous discussion, despite some services like minimizing charging cost could be done by individual EV, in most cases, these services can be practical in place only provided by a large fleet of EV. As shortly mentioned above, FO is widely proposed to aggregate the large penetration of EVs in the near future (FO used in the Edison project: <http://www.edison-net.dk/>). Firstly, the roles of the FOs are summarized from the literature; then we show the relationships between the FOs and other actors in a smart grid context; further discussion is made on the communication standard used for implementing the charging schedules.

3.1 Role of FOs

Tomas et al. [4] proposed two new electricity market agents: the EV charging manager and the EV aggregator/FO which are in charge of developing charging infrastructure and providing charging services, respectively; based on this, the authors proposed a regulatory framework for charging EVs. Similar concept is introduced in [32], where the concept of EV service provider (EVSP) is discussed. In [32], the EVSP has two functions: one is responsible for installing and operating the charg-

ing equipment, another is supplying electricity to the EVs. In term of the feasibility of applying the FO concept, Bessa and Matos [3] gave a literature review regarding the economic and technical management of an aggregation agent for electric vehicles. The reviewed papers are organized into three technical categories: electricity market and EV technical and economic issues; aggregation agent concept, role and business model; algorithms for EV management as a load/resource.

It is observed that the main difference between the proposed solutions of FO lies on whether the FO has twofold functions or sole function, i.e., some studies assumed that a FO functions as both charging equipment supplier and charging service provider, others only refer FO as the charging service provider. Although various differences exist in the details of the proposed FO concepts, they are assumed to achieve the same goals in this study, regardless the ownership of the charging equipment:

- Guarantee driving needs of the EV owners with optimal management of EV charging;
- Provide ancillary services to power system operators with optimal allocation of EV fleet resources.

3.2 Service relationships between FOs and other actors in a smart grid

Fig.1 illustrates the relationships between FOs and other actors in a smart grid by showing the services that FOs can provide to them.

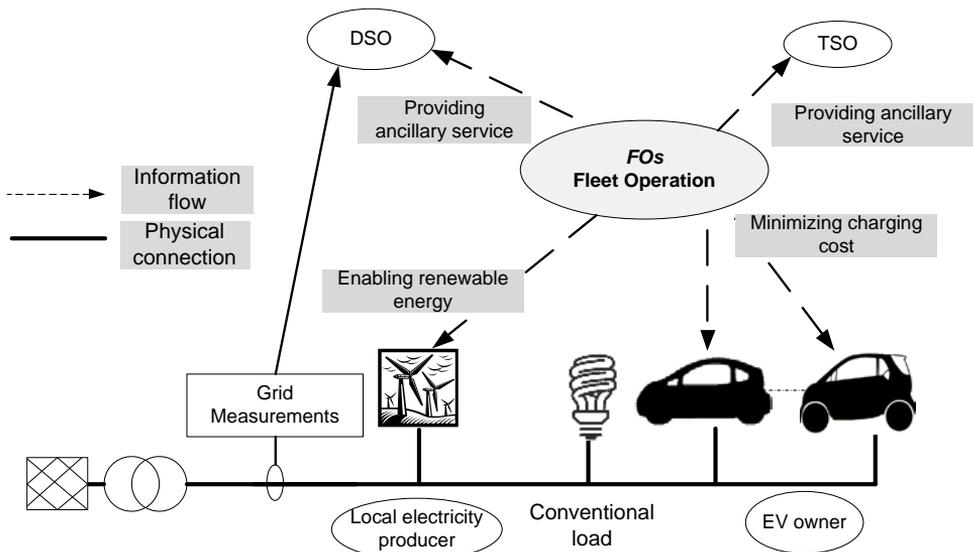


Fig.1: The services relationships between FO and other actors in a smart grid.

Note that the relationship between FOs and EVs is a slightly more complex. From one perspective, FOs need to attract the participation of EVs and then have the ability to provide services to other actors in the smart grid; from another perspec-

tive, FOs can provide the service of minimizing charging cost to EVs which help the EV owner to save money. Therefore, FO may need to consider many factors rather than purely make benefits when providing services to EVs.

3.3 Implementing the charging services/schedule provided by FOs

With the purpose of illustrating how the charging schedule is implemented, this section discusses the relevant communication standard for integrating EVs into the distribution grid. For example, the studies in [12], [13], [19], [22] focus on generating the optimal charging schedule instead of implementing it. These parts are supplemented by the works in [33]-[37]. It is noted that the purpose is to provide the relevant/widely used communication standard which can support the EV smart charging rather than comparing the various communication standards. Su et al. [33] presented an overview of EVs from the perspectives: 1) charging infrastructure (society of automotive engineers standard) and Plug-in Hybrid Electric Vehicles (PHEVs)/Plug-In Electric Vehicles (PEVs) batteries, 2) communication requirements. In European area, studies in [34]-[37] recommended the IEC standards which are illustrated in Fig.2. The objectives of all the studies [34]-[37] are the realization of a standardized communication interface, the vehicle to grid communication interface. The standardization will make it possible for users of EVs to have easy access to EV charging equipment (EVSE) and related service throughout Europe. EVSE refers to all the devices installed for the delivery of power from the electrical supply point to the EV. EVSE supports the smart charging functions. The decision can be made on the EV level or on the FOs level. The IEC 15118 is the most recommended communication standard in the work [34]-[37] and demonstrated in details in [34], [35] by showing the sequence diagram of a charging process between the EVSE and the EVs. For the communication between the EVSE and the FOs, it is recommended that IEC 61850 can fulfil the functions.

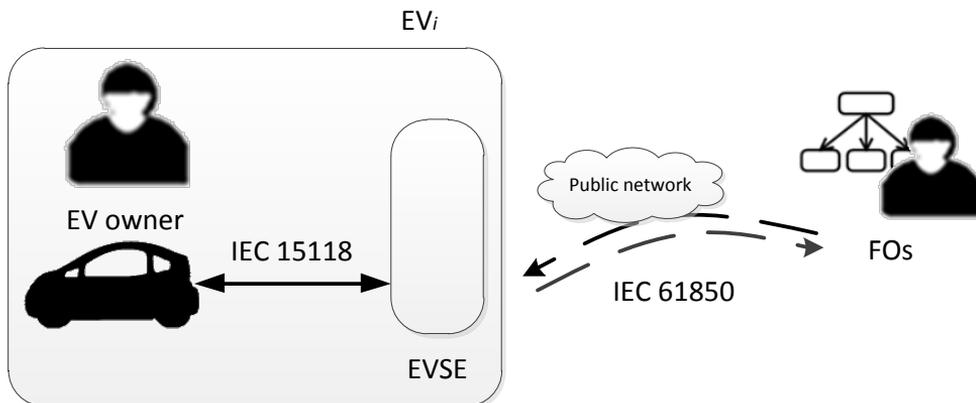


Figure 2: Relevant ICT standards support the EV smart charging in the context of smart grids

In general, we define EV_i as the combination of the EVSE and the EV as well as holding the intelligence endowed by the EV owner (illustrated in the Fig.2). With

this background, for the next parts of this paper, we will review the control architectures, the algorithms which are used by FOs in the literature and the communication part will be ignored.

4 CONTROL ARCHITECTURES AND THEIR INTEGRATION

4.1 Centralized charging control of EV FO

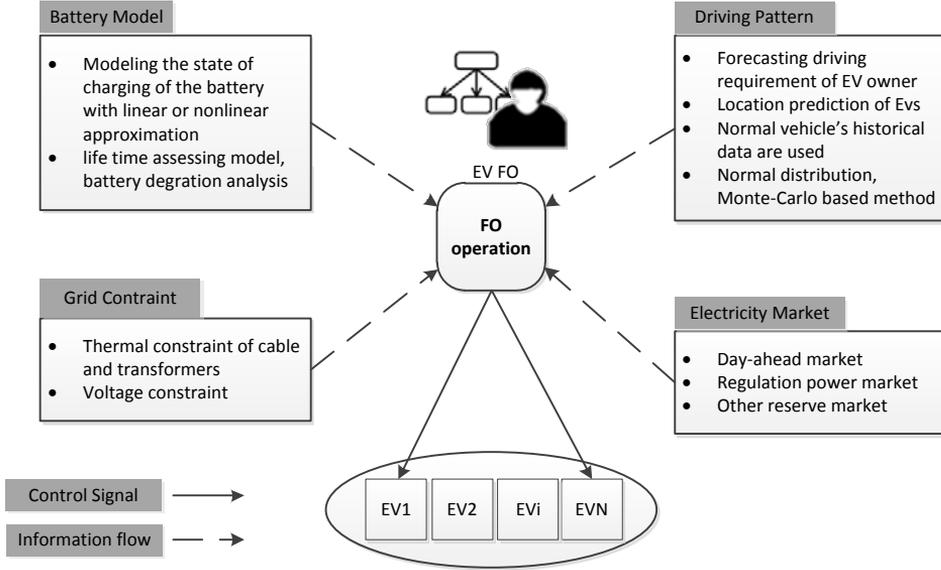


Figure 3: Primary inputs and output of EV FO.

Fig. 3 mainly depicts the four inputs when making the control strategies. In this context, FO obtains all the relevant information including the EV battery model, the EV driving patterns, the grid constraint and the electricity price and centrally makes the charging schedule for each EV. In contrast, some EV owners want to generate the charging schedule by themselves, this is called decentralized control. However in the context of decentralized charging, the FO still needs to coordinate the grid constraints with the EV owners and this coordination is usually implemented by using price signal. In the following section, we will present two methods of implementing decentralized charging control as well as respecting to the grid constraint.

4.2 Decentralized charging management of EV FO

The scheme of the information flow in decentralized charging control is presented in Fig.4.

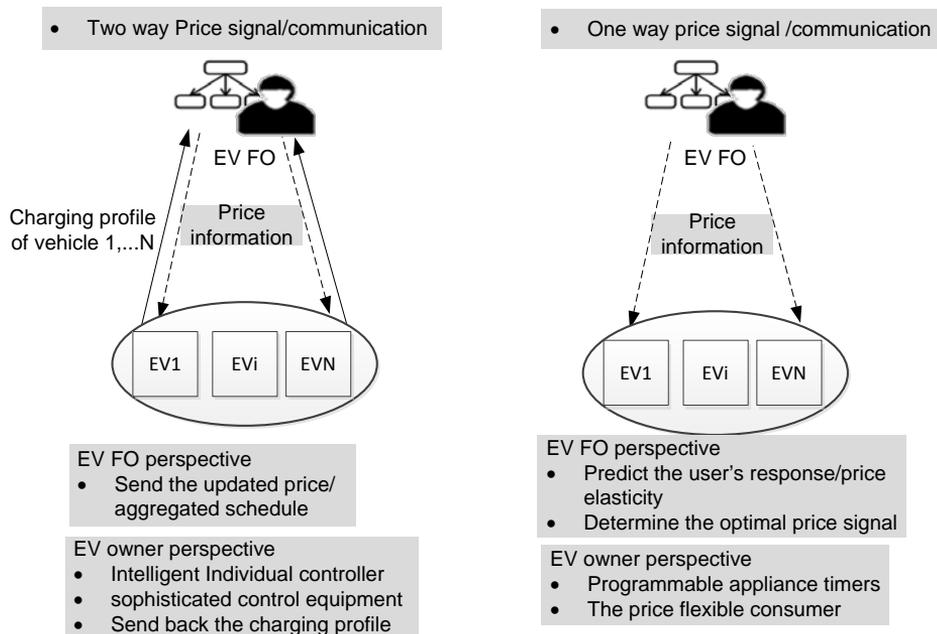


Figure 4: Schematic view of the information flow between the FO and the EVs.

In Fig.4, two kinds of price signals are presented. For the left figure, i.e., two way price signal, this is also used such as game theory, valley filling. The basic idea is that EVs update their charging profiles independently given the price signal; the FO guides their updates by altering the price signal. Several iterations are required for the implementation. For the right figure, we call it one way price signal method; this method requires FO to predict the users' response to the prices. The price signal can be designed simply as time-of-use price or more dynamic prices.

4.3 Comparison between control strategies

Table 2 compares the two control methods based on literature review. We first clarify the terminologies used in this study: centralized control and decentralized control are regarded as architectures, which mean the charging schedule decision is made either in upper FO level or local EV controller level. Direct control means that FO sends the control signal to the EVs and the EVs executes the charging schedule. Price control means that the FO coordinate their requirements (distribution grid constraints) by sending electricity price to the EV controller and the EV controller takes the decision to generate the charging schedule. This is indirect control for the FO because the FO is only specifying a constraint (the price) for the charging schedule and not the charging schedule itself.

Table 2: Comparison between direct control and price control strategy

	<i>Control Methods</i>	
	<i>Direct control</i>	<i>Price control</i>
<i>Features of the control method</i>	<ul style="list-style-type: none"> • Control signals (i.e., set points) • High level controller makes the decision 	<ul style="list-style-type: none"> • Price incentive • Consumer make decision
<i>Advantages</i>	<ul style="list-style-type: none"> • High certainty • Better optimal results 	<ul style="list-style-type: none"> • Privacy improved • Less communication cost
<i>Disadvantages</i>	<ul style="list-style-type: none"> • Inflexible • High communication cost • High computation requirement 	<ul style="list-style-type: none"> • Lower certainty • Better knowledge on customer's response to price required

5 DATA ANALYSIS OF BATTERY MODEL, DRIVING PATTERN

5.1 Battery model

Basically, there are two ways to model the charging characteristics of the EV, i.e., the battery model. One is an individual battery pack model, another is aggregated (characterize the state of charge of an EV fleet in one model). For simplicity, most of the studies considered EV as a battery pack when investigating the optimal charging and discharging problem. Currently, most battery model studies [38]-[40] focus on three different characteristics:

- The first and most commonly used model is termed as a performance or a charge model and focuses on modelling the state of charge of the battery, which is the single most important quantity in system assessments.
- The second type of model is the voltage model, which is employed to model the terminal voltage so that it can be used in more detailed modelling of the battery management system and the more detailed calculation of the losses in the battery.
- The third type of model is the lifetime model used for assessing the impact of a particular operating scheme on the expected lifetime of the battery.

We give further discussion on the first model, usually, linear and nonlinear approximation are used to characterize the state of charge of the battery. Linear approximation are utilized in works [19]-[21] to approach the charging behaviour of an EV battery. Rotering and Ilic [12] considered a nonlinear battery model. The studies [20], [21] has shown that violations of the battery boundaries when applying the charging schedule based on the linear approximation are relatively small, i.e., less

than 2% of the usable capacity. The benefit of using a nonlinear approximation does not justify the increase in computation time.

5.2 Driving pattern

The analysis of driving pattern can be divided into two main directions:

- Utilization of EVs, in other words, a typical user daily life means that at any point during the day an EV could possibly be in the garage, in an employer's parking lot, in a store parking lot or on the road. This means that the aggregator needs to characterize/predict the driving pattern of EVs.
- Location of EVs when charging and how many of them will be charged at a time, since such driving patterns produce an impact on the distribution grid.

In most papers [19]-[21] the authors assume that the aggregator know the users' driving patterns. There are few studies on investigating the driving pattern issue. Kristoffersen et al. [22] investigated the method to construct driving patterns with the historic data in Danish case. By clustering the survey data on the vehicle fleet in Western Denmark (January 2006-December 2007), a representative driving patterns for each vehicle user are constructed. S. Shahidinejad et al. [41] developed a daily duty cycle which provides a complete data set for optimization of energy requirements of users and furthermore, this information can also be used to analyse the impact of daytime charging by a fleet of plug-in electric vehicles on the electric utility grid that may create a peak demand during the day to be met by the local utility grid. Normally, intra city or short term driving patterns are largely predictable due to fixed working hours and fixed business schedules and routes.

6 MATHEMATICAL MODELING AND CONTROL: CENTRALIZED CONTROL

In this section, we will present algorithms often used for the centralized control. Linear programming, quadratic programming, dynamic programming and stochastic programming will be shown for the discussion through an extensive literature review. Further, a qualitative comparison among the four algorithms will be presented in the end of this section.

6.1 Linear programming (LP)

Sundstrom and Binding [20], [21] used linear approximation to characterize the state of charge of a battery and formulate the charging process for an EV fleet into a linear programming based optimization problem:

$$\min t_s c^T P_b \quad (1)$$

Subject to

$$\begin{cases} A_s P_b \geq b_s \\ A_g P_b \geq b_g \\ A_b P_b \geq b_b \\ b_l \leq P_b \leq b_u \end{cases} \quad (2)$$

With the time slot t_s , cost vector c , the charging power P_b , the stopover inequality constraints (A_s, b_s) , the generation inequality constraints (A_g, b_g) , the battery inequality constraints (A_b, b_b) , and the upper and lower bounds (b_u, b_l) . The solution of this linear optimization problem is the optimal charging profile while minimizing the charging cost of EV fleet.

6.2 Quadratic programming (QP)

A nonlinear approximation (quadratic formulation) of the battery charging model is also studied in [20], [21]. The results showed that the number of constraints is higher and increases faster with a growing fleet in the quadratic formulation than in the linear formulation, the difference in calculation time increase with increasing fleet size. An example is conducted for comparison and the result indicated that calculating time using the quadratic formulation is 819 times the calculation time using the linear formulation. But the result difference does not justify the benefits of using quadratic formulation. Another example of using quadratic programming method was introduced by Kristien et al. [30] who formulated the power loss problem caused by large penetration of EVs in the grid into a sequential quadratic optimization problem. The objective is to minimize the power losses which are treated as a reformulation of the nonlinear power flow equations. The charging power obtained by the quadratic programming cannot be larger than the maximum power of the charger P_{max} . The batteries must be fully charged at the end of cycle, so the energy which flows to the batteries must equal the capacity of the batteries C_{max} . x_n is zero if there is no EV connected and is one if there is an EV connected at node n . The above problem specification can be represented as follow:

$$\min \sum_{t=1}^{t_{max} \text{ lines}} \sum_{l=1} R_l \cdot I_{l,t}^2$$

Subject to

$$\begin{cases} \forall t, \forall n \in \{nodes\}: 0 \leq P_{n,t} \leq P_{max} \\ \forall n \in \{nodes\}: \sum_{t=1}^{t_{max}} P_{n,t} \cdot \Delta t \cdot x_n = C_{max} \\ x_n \in 0,1 \end{cases} \quad (3)$$

The quadratic programming techniques are applied using both deterministic and stochastic methods in Kristien's paper. The input variables in both cases are the daily/hourly load profile. In the deterministic case, the load profiles are static. In

the stochastic case, the load profile are transformed into probability density functions, which means that the fixed input parameters are converted into random input variables with normal distributions assumed at each node. The details of stochastic case are presented in the following section.

6.3 Dynamic programming (DP)

Dynamic programming is widely used in many papers [12], [13], [23], [30] with different purposes. We introduce the work in [12]. In the paper, a specific control strategy is denoted by

$$\pi = \{u_0, u_1, \dots, u_k, \dots, u_{N-1}\}$$

Where u_k is the control variable denotes a dimensionless and discrete representation of P_k . P_k corresponds to the purchased power flow. The total cost of a whole charging sequence, J^π is then given as below:

$$J_0^\pi(x_0) = J_N(x_N) + \sum_{k=1}^{N-1} l_k(x_k, u_k, k)$$

J^N means cost of the final step, $l_k(\cdot)$ denotes the cost-to-go for all other steps, N denotes the total number of time intervals. The objective is to find the optimal control variables which can minimize the total cost. The detailed mathematic formula of cost of final step and cost-to-go are not presented here. The purpose of the function used for calculation of cost of final step is ensuring that the battery is fully recharged before the first trip of the following morning. For the function of cost-to-go, the electricity price, regulating-up price and regulating-down price are considered.

This is a classical dynamic programming formulation and the optimal trajectory is calculated starting with the cost of the last state and going backwards through time until the first state's optimal cost $J_0^0(x_0)$ is given by the algorithm. Concerning the computing time of dynamic programming, the results in [30] show that the difference of the charging profiles for the QP and DP technique are negligible, however, considering the computational time and storage requirements, the storage requirements are heavier for the DP technique compared to the QP technique, hence, the computational time for DP technique is longer.

6.4 Stochastic programming

Most of the current researches [12], [19], [21] assume that the load profiles, initial state of charge, driving pattern, grid conditions and electricity price are known and determined to the FO, however, this is certainly not the case in the reality. It is therefore necessary to put efforts on stochastic approach to reduce the risks, and some works have been done recently [30], [42]-[45].

A stochastic approach for calculation of the daily load profiles is considered in [30] when minimizing the power loss problem. A sample average approximation meth-

od [46] is utilized to formulate the random inputs and the lower bound estimate principle is used to estimate the optimal value. It is noted that the model is the same as presented in equation (3) of this section (section 6.2). The uncertainties of these parameters can be described in terms of probability density functions. In that way, the fixed input parameters are converted into random input variables with normal distributions assumed at each node. N independent samples of the random input variable ω^j , the daily load profile, are selected. Following equation (4) gives the estimation for the stochastic optimum \hat{v}_n . The function $g(P_{n,t}, \omega^j)$ gives the power losses and $P_{n,t}$ is the power rate of the charger for all the EVs and time steps. \hat{f}_N is a sample-average approximation of the objective of the stochastic programming problem:

$$\hat{v}_n = \min\{\hat{f}_N(P_{n,t}) \equiv \frac{1}{N} \sum_{j=1}^N g(P_{n,t}, \omega^j)\} \quad (4)$$

The mean value of the power losses, $E(\hat{v}_n)$, is a lower bound for the real optimal value of the stochastic programming problem, v^* , as shown in the below:

$$E(\hat{v}_n) \leq v^*$$

$E(\hat{v}_n)$ can be estimated by generating M independent samples $\omega^{i,j}$ of the random input variable each of size N . M optimization runs are performed in which the non-linear power flow equations are solved by using the backward-forward sweep method. The optimal values of M samples constitute a normal distribution:

$$\hat{v}_n^j = \min\left\{\hat{f}_N(P_{n,t}) := \frac{1}{N} \sum_{i=1}^N g(P_{n,t}, \omega^{i,j})\right\}, j = 1, \dots, M.$$

\hat{v}_n^j is the mean optimal value of the problem for each of the M samples. $L_{N,M}$ is an unbiased estimator of $E(\hat{v}_n)$. Simulations indicate that in this type of problem, the lower bound converges to the real optimal value when N is sufficiently high:

$$L_{N,M} = \frac{1}{M} \sum_{j=1}^M \hat{v}_n^j.$$

A forecasting model for the daily load file for the next 24 hours is required at first, then the daily profile of the available set are varied by a normal distribution function. The standard deviation σ is determined in such a way that 99.7% of the samples vary at maximum 5% or 25% of the average. In general, the simulation results indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.

Other studies such as Fluhr et al. [42] use Monte-Carlo method to generate the probability distributions of the driven travel paths for one week with the survey "Mobility in Germany" (MIG), because the original data MIG only provide one day driving behavior; studies in [43]-[45] use normal distribution and Poisson distribution to investigate the probabilistic distribution of plugin time and initial state of charge of EVs.

6.5 A summary of the presented algorithms with three types of criteria

In table 3, we mainly summarize the information of the presented algorithms in term of the computation time, the certainty of performance, and the applicability. The summary aggregates the comparisons described in the literatures in term of computation time and performance of the presented algorithms. Besides, the applicability of the presented algorithms is summarized from two perspectives.

Table 3: General comparison between the presented algorithms

	<i>Computation time</i>	<i>Certainty of Performance</i>	<i>Applicability in general</i>	<i>Applications to EV charging</i>
<p><i>Linear programming</i></p> <p>Used in: [19], [20], [21].</p>	<p>Generally, it is the fastest.</p>	<p>Results in [19], [20], [21] showed that the performance is excellent in term of finding the optimal solution.</p>	<p>1) The objective function is linear, and the set of constraints is specified using only linear equalities and inequalities.</p> <p>2) Standard model, easy for implementation.</p>	<p>Minimize charging cost of EVs.</p>
<p><i>Quadratic programming</i></p> <p>Used in: [20], [21], [30].</p>	<p>Ref. [20] showed that the calculation time using the QP is 819 times than the one using LP for a fleet of 50 vehicles.</p>	<p>Ref. [20] showed that the difference between using LP and QP is minor. Therefore, the benefit of using the QP does not justify the increase in computation time.</p>	<p>1) The objective function has quadratic terms, while the feasible set must be specified with linear equalities and inequalities.</p> <p>2) Standard model, easy for implementation.</p>	<p>1) Minimize charging cost of EVs.</p> <p>2) Minimize power losses of power systems.</p>
<p><i>Dynamic programming</i></p> <p>Used in: [12], [13], [23], [30].</p>	<p>Ref. [30] indicated that the computational time for DP is slower compared to QP.</p>	<p>Ref. [30] showed that the difference between the charging profile of using QP and DP is negligible, although the QP gave more accurate results.</p>	<p>1) Studies the case in which the optimization strategy is based on splitting the problem (EV charging schedule) into smaller subproblems (multi-time slots).</p> <p>2) No standard model, difficulty increases for complex problem.</p> <p>3) Give global optimal result.</p>	<p>1) Minimize charging cost of EVs.</p> <p>2) Minimize power losses of power systems.</p> <p>3) Maximize profit of providing regulation services.</p>
<p><i>Stochastic programming</i></p> <p>Used in: [30], [42], [43], [44], [45].</p>	<p>The computation time is longer generally because more scenarios are considered.</p>	<p>The simulation results in [30] indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.</p>	<p>Studies the case in which some of the constraints or parameters (Load profile, driving pattern etc.) depend on random variables.</p>	<p>1) Minimize charging cost of EVs.</p> <p>2) Minimize power losses of power systems.</p> <p>3) Maximize profit of providing regulation services.</p>

7 MATHEMATICAL MODELING AND CONTROL: DECENTRALIZED CONTROL

Compared to centralized control, the decentralized control is a relative new application to EV fleet control, but still a lot of efforts have been done considering the amount of the articles.

7.1 Two way price signal- Price and power negotiation

As discussed in section 3, the following papers [7], [47]-[51] are chosen to further illustrate the two way price signal control method. Considering the similarities of the papers, we will discuss and present the papers in the following: the detailed formulas are given in the first paper with the purpose of facilitating reader's understanding. In paper [7], decentralized charging control of large population of electric vehicles is formulated as a class of finite-horizon dynamic games. Within this game, the control objective is to minimize electricity generation costs by establishing an EV charging schedule that fills the overnight demand valley. Moreover, the paper establishes a sufficient condition under which the system converges to the unique Nash equilibrium.

The key formulas are listed below:

$$x_{t+1}^n = x_t^n + \frac{\alpha^n}{\beta^n} u_t^n, t = 0, \dots, T - 1$$

Where x^n is the state of charge of EV_n , α^n and β^n means the charging efficiency and battery size of EV_n , and u^n represents the local control variable. The purpose of the study is to find the set of feasible full charging controls, which are described below:

$$\omega^n := \{u^n \equiv (u_0^n, \dots, u_{T-1}^n); s. t. u_t^n \geq 0, x_T^n = 1\}$$

Where the final constraint on x_T^n requires that all EVs are fully charged by the end of the interval. The cost function of agent n, denoted by $J^n(u)$ is used as criteria and specified as:

$$J^n(u) := \sum_{t=0}^{T-1} \{p(r_t)u_t^n + \delta(u_t^n - avg(u_t))^2\}$$

Where each agent's optimal charging strategy must achieve a trade-off between the total electricity cost $p(r)u^n$ and the cost incurred in deviating from the average behaviour of the EV population $(u^n - avg(u))^2$. With these criteria and certain conditions, the theorem about the existence of the Nash equilibrium is presented in the paper.

The proposed algorithm ensures convergence to a flat, or optimally valley filling aggregate charging profile. However, in both papers [47], [48], all EVs are required to participated the negotiation at the same time, and implement the schedules they

commit to. In a more realistic scenario, EVs may join the negotiation at different time, not necessarily known to the FO beforehand. Furthermore, the approach is suitable to today's system or those mainly comprised of conventional demand, this limits the cycling required in thermal plants; however the response to intermittent generation will be of more interest. During periods of intermittent (renewable) generation (RG), the price is unlikely to be directly related to demand, as RG typically has lower or zero marginal cost.

Zhong Fan [50] applied the concept of congestion pricing in internet traffic control and showed that price information is very useful to regulate user demand and consequently balance the network load. Individual users adapt to the price signals to maximize their own benefits. User preference is modelled as a willingness to pay parameter which will influence both individual charging rate/cost and overall system behaviour, because, the unit price of energy in a time slot is a function of the aggregate demand in the paper. Charging power is allocated according to fair pay principle which is economically efficient and the mechanism ensure the system stable under arbitrary network topologies. However, the approach is not compatible with current market structure since in Zhong Fan's paper, iterative convergence is required. Besides, the assumption that price is a function of demand, with a fixed constant of proportionality is weak, because reductions in demand won't necessarily lead to corresponding reductions in price. Moreover, only the EV load is considered in the paper, it is arguable to inquiry the conventional load. As mentioned by the authors in the paper, the proposed model is also a kind of game theory.

In short conclusion, both papers [49][50] made a good effort in trying to use game theory to formulate the complex decision making process for future energy traders, especially the FO. In the future smart grids, the distributed generation resources (DER) are most likely to be integrated via market-based mechanisms; therefore game theory will be a very useful tool to study the dual impacts between DERs and the markets.

7.2 One-way price signal-Price and demand elasticity

By using one-way price signal, we mean that the EVs controller do not need to propose and submit their charging profile to the EV FO, instead the FOs will anticipate their response to the dynamic price. The dynamic price ranges from simple time-of-use electricity rate [52][53] to more varying hourly prices [54][55]. Both studies [52][53] suggested that the TOU rates can be properly designed to reduce the peak demand as EVs penetrate the vehicle market. However, it is also noted in [52] that the extent to which properly designed rates could assist in maintaining grid reliability will remain open until empirically tested EV owner's price responsiveness through experiment pilots are known.

Both studies [54][55] investigated the price elasticity of electricity consumers and these are also the key issues in one-way price signal approach. Details in [55] is

presented. In the model [55], the marginal utility function of loads is realized by the following parametric stochastic process:

$$r(t) = \begin{cases} \beta - \delta(t - \alpha), & \alpha \leq t \leq \alpha + \gamma; \\ 0, & \textit{otherwise}. \end{cases} \quad (4)$$

where $\alpha, \beta, \gamma, \delta$ are random variables that describes the different characteristics of utility function as follows:

- a) α stands for the time slot that a task is initially requested, which also reflects the task distribution;
- b) β is the initial marginal utility, which stands for the magnitude of the marginal utility.
- c) γ is the tolerable delay, which determines the maximum delay that a user can tolerate to finish a task;
- d) δ means the utility decay rate, which represents the cost of inconvenience by the delay.

Under this model, the scheduling of each individual task is now a random event whose probability distribution is controlled by the stochastic process $r(t)$. The aggregated demand curve can be estimated through expectation with respect to the distribution of $r(t)$. Note that some assumptions have been made before, such as the time period of the scheduling is divided into T time slots, the total M individual tasks $m: m=1, \dots, M$ of different appliances that are to be initialized by all the users within the scheduling period, and each task will consumer x_m kWh energy. Furthermore, it is assumed that each task can be completed within one time slot; therefore, tasks that have duration longer than one time slot will be decomposed into multiple tasks that are considered independently.

In general, one can see that within decentralized control, no significant computing resources are required and the communication infrastructure is also simplified compare to centralized control.

8 CONCLUSION AND RECOMMENDATIONS

8.1 Conclusion and discussions

As a conclusion, it is learned from this study that:

- Control objectives of aggregating a large penetration of EVs are essential for the starting of generating EVs' schedules.
- Linear approximation of state of charge of battery (EV) is acceptable when doing the smart charging study.
- Linear programming is suitable for the smart charging study of EV fleet and individual EV.

- Price signal can be well designed and utilized to coordinate the charging profiles of EVs.

The following benefits of present study can be identified:

- The study outlines a foundation for future improvements in term of smart charging from a control theory perspective.
- The advantage and disadvantage of centralized and decentralized control are discussed, which gives a basis for comparing available methods for future developments.
- Details modelling method and algorithms are illustrated by showing the key formulas and compared in term of their performance, calculation time etc.

However, it should be observed and emphasized that the above discussion did not consider the real time operations, i.e., there is no continuous monitoring and assessment of the state of dynamic system and therefore lack of the appropriate response in abnormal situations. This means that new procedures considering the dynamic behaviour of EV fleet and distribution networks should be developed as well.

8.2 Recommendations on future research directions in the area

Based on the discussions in the present study, future research directions are outlined below:

1) Coordinate the multi-goals of smart charging of EVs

Recently, the trend in smart charging of EVs is to integrate the interests of EV owners, ancillary services required by the transmission system operator as well as respecting the hard constraint imposed by the distribution system operator. Research in [9] [21] aim to coordinate these multiple objectives centrally. Alternatively, some studies [56] used a price signal/market approach to coordinate the multiple objectives.

2) Integrating the control method

Although most research assumed either centralized control or decentralized control methods when starting the study, this is indeed an important decision which should be taken in the earlier stage. From our perspective, three issues shall be investigated thoroughly.

- Depending on the aggregation goals, this is due to different goals have various requirement on EVs in term of response time etc.
- Depending on the EV consumer's participation, such as some consumers do not like their EVs to be controlled by FOs, under such circumstance, price incentives are a suitable method.
- Depending on the business model, we means whether the economic benefits of optimal charging of EVs can justify the cost of communication in-

frastructure in all cases; this will be an important consideration when choosing the control method.

Studies in [57], [58] compared the centralized control and decentralized control method when utilizing them to make an optimal plan which can optimal delivery energy to EVs as well as avoiding grid congestions. They outlined the advantages and disadvantages of both strategies. Fig. 5 illustrates the structures of integrating control strategies in a smart grid environment especially considering the congestion management in distribution networks. The argument for proposing this integration relies on the fact that this system architecture is comprehensive for the solution of integrating EVs into the power distribution systems.

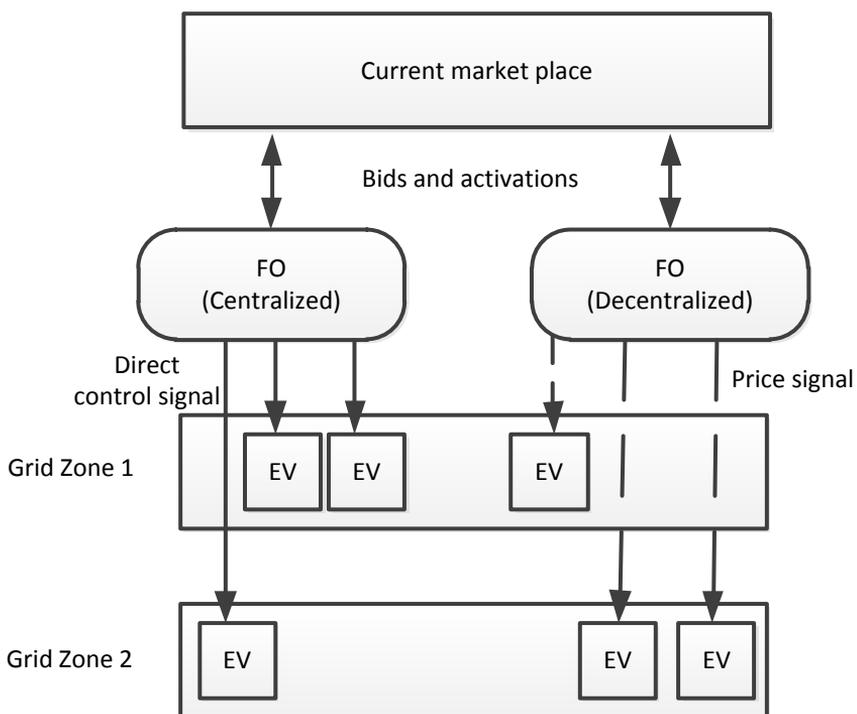


Figure 5: Integrating control method considering grid congestion management

3) A multi-agent systems based realization of smart charging of EVs

It is observed that when implementing both control strategies of smart charging of EVs, especially decentralized control method, multi-agents system based technology is very suitable to design a coordinated and collaborative system for an intelligent charging network of EVs. In the multi-agent systems, different interests of various actors shown in Fig.1 can be presented and coordinated by using smart charging method. By using multi-agent systems technology, one can model the optimizations and the negotiations happened in the smart charging of EVs. In [58],

[59], the authors modelled the smart charging of EVs using multi-agent systems technology.

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A.2 Optimal charging schedule of an electric vehicle fleet

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Optimal Charging Schedule of an Electric Vehicle Fleet

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Abstract—In this paper, we propose an approach to optimize the charging schedule of an Electric Vehicle (EV) fleet both taking into account spot price and individual EV driving requirement with the goal of minimizing charging costs. A flexible and suitable mathematic model is introduced to characterize the smart charging behavior and detailed parameters needed for charging behavior of an individual EV are analyzed. The individual charging schedule is extended to the EV fleet. Simulation results are presented to illustrate the effectiveness of the proposed model.

Index Terms—Electric Vehicle, Fleet Operator, Charging Schedule, Linear Program

I. INTRODUCTION

The Danish government has issued a long-term energy policy aiming at 30% production from renewable energy and 50% of the average electricity consumption from wind power by 2025 [1]. This policy conforms well to the procedure of dealing with global environmental issues and has led to a growing interest in EVs. EVs have V2G and G2V capabilities which can be used as a storage device for smoothing wind power fluctuations and to provide more reliable power operation as well as presents flexible demands.

Several investigations have been made to reach the goal of this new Danish energy policy, Larsen et al. [2] proposed scheme to improve system operations, which considered EVs as new power consumers and also the possibilities as providers of energy storage. The possibility of using vehicle to grid to improve wind power integration was studied in [3] and the result suggested that a small share of EVs may partially diminish the short period oscillations, while a high share of EVs achieved much better improvements. A feasibility study of implementing V2G scenario in Denmark was done in [4][5]. The system constraints for integrating EVs into power systems were examined in the study and the technical and economical viability of various possible V2G architectures were evaluated. It was concluded that the V2G technology can assist in realizing the goal of Danish government. In addition to these feasibility studies, a V2G demonstration project was implemented by AC Propulsion Inc. to evaluate the practicality of EVs providing regulation services [6].

Extensive research about EV optimal charging management have been conducted around the world in recent years. As early as 1983, Heydt [7] researched the impact of EV deployment

on loads and proposed the methods to alleviate peak loading with off-peak recharging and the shift of peak loads to off-peak periods. Koof et al. [8] presented an extensive study on controlling an EV energy system to reduce the fuel consumption and exhaust emissions with three algorithms, dynamic programming, quadratic programming and model predictive control. Kristien et al. [9] researched the impact of charging PHEVs on a residential distribution grid and illustrated the results of coordinated and uncoordinated charging. Niklas et al. [10] proposed two algorithms to address optimal charging control to avoid the peak load, one is to optimize the charging time and energy flow, another is generating profits by participating ancillary service markets which can alleviate the peak load. Sundstrom and Binding [11] established charging plan to optimize the cost as well as achieve optimal power balancing. In [12], Kristoffersen presented a framework for optimizing electric drive vehicles charging and discharging given variations in electricity spot prices and driving patterns of the vehicle fleet. However, some methods lack the flexible ability to adapt to any driving pattern since most of these methods are based on an hourly charging scenario, some methods did not present a simple and effective way to formulate and solve the optimal charging problem of EV fleets, and most of them investigated the problem from the overall availability of the EV fleet instead of from the individual EVs perspective.

The purpose of this paper is to investigate methods of obtaining the optimally individual EVs charging schedule and the charging schedule of an EV fleet and test it with realistic data. Detailed model is used to address the individual charging schedule and is then extended to an EV fleet. Based on predicted data including driving pattern information [13] and electricity spot price, the day-ahead charging schedule of an EV fleet is obtained by linear programming. The paper is organized as follows: Section II describes the system architecture of a fleet operator and some assumptions. In section III, we present methods to formulate the problem and get the individual charging schedule. The methods are extended to a large scale of an EV fleet in section IV. Simulation results are illustrated in Section V. Finally, concluding remarks are collected in Section VI.

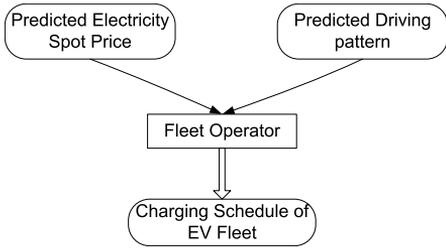


Fig. 1. System architecture of fleet operator

II. SYSTEM ARCHITECTURE AND ASSUMPTIONS

Nowadays, it is widely accepted to charge the EV batteries with mainly three options [14]:

1. Fast charging: pull over EVs at the fast charging stations and charge the EV batteries within, e.g., 10-15 minutes.

2. Battery swapping: drive EVs to the battery swapping stations and exchange the used battery with a fully charged one.

3. Low power charging: charge EVs at homes, parking lots near home, working place or shopping malls.

The third option is analyzed for this paper, by introducing more advanced communication equipments, a centralized control system fleet operator is used for the interactions between the EVs and the electricity market. The overview system architecture of the fleet operator is depicted in Fig.1. The fleet operator need historical or statistic data of all the EVs and electricity spot price in order to predict spot price and driving pattern for next day. In this paper, we will not investigate the way of forecasting these data, the fleet operator is assumed to obtain the predicted electricity spot price and driving pattern. In term of relevance of the predicted electricity spot price, the Nordic electricity market is ideally suited for the application of optimal charging control with fleet operator for its day-ahead spot market price. Some researches [15][16][17] have been done on forecasting the electricity price in the Nordic electricity market. Thus it is reasonable for the fleet operator to predict the spot price for next day and to manage the optimal charging behavior according to user's preference.

Some assumptions are given for the fleet operator before we start to formulate and analyze the problem:

- Based on a previous study [11], the difference is relatively small between of charging schedule based on a linear approximation battery model and a quadratic approximation battery model. A Linear battery model is chosen for simplicity in this paper.

- Charging power is constant.
- The economic impacts of depth of discharge (DOD) to the battery life are ignored.
- Energy content E_0 , i.e. initial status of battery SOC_0 is assumed to be known, the state of charge (SOC) is the relative energy level

$$SOC = \frac{E_t}{E_{cap}} \cdot 100\%$$

where E_t is the available energy of the battery in time t , E_{cap} is the rated capacity of the battery.

III. METHODS

In this section, we analyze the optimal charging process with the goal of minimizing the charging cost when getting the day-ahead charging schedule of an EV fleet. The individual's optimal charging process is considered first since the charging schedule should be in accordance to their requirements. With the constant charging power ability, this problem can be formulated as a linear one:

$$\min C^T E$$

subject to

$$\begin{cases} A_t E \geq B_e \\ A_t E \leq B_b \\ A_t E \geq B_{set} \\ 0 \leq E \leq E_{max} \end{cases} \quad (1)$$

with the cost vector C , the decision variable vector E , the stop-over inequality constraints (A_t, B_e) , the battery inequality constraints (A_t, B_b) , the inequality constraints (A_t, B_{set}) and the upper and lower bounds $(0, E_{max})$. The first constraint means that the available energy in battery should be greater than or equal to the energy requirement for the next trip. The second constraint indicates that available energy in battery should be less than or equal to the maximum power capacity. The third constraint requires that the planning charge energy should accord to the user's special preference. The last one represents that the planning charge energy should less than its charging ability.

Assume $j = 1, 2, \dots, n, \dots, N$ is the index for the time slot contained in one plan duration. $k = 1, 2, \dots, m_j$ is the index for the stop-over contained in one time slot j . Therefore, the cost vector C comprises the cost concerning the time slot j and stop-over index k , $C_{j,k}$. The charging energy vector E comprises the charging energy for each time slot index and stop-over index $E_{j,k}$.

$$C = \begin{bmatrix} C_{1,1}, C_{1,2}, \dots, C_{1,m_1}, \dots, C_{N,1}, C_{N,2}, \dots, C_{N,m_N} \end{bmatrix}^T \quad (2)$$

$$E = \begin{bmatrix} E_{1,1}, E_{1,2}, \dots, E_{1,m_1}, \dots, E_{N,1}, E_{N,2}, \dots, E_{N,m_N} \end{bmatrix}^T \quad (3)$$

As we assumed before, individual's driving pattern is predicted, which means the following information is available for each EV:

- ◊ Time of stop-over $t_{stop,j,k}$
- ◊ Time of disconnection (driving time) $t_{drive,j,k}$, the k is the same one with the stop-over index.
- ◊ The time loss during the process of connecting the car to the grid is ignored when the driving procedure is finished and the connection time is assumed equal to the stop-over time.

◇ Energy requirement for the next trip $E_{drivej,k}$. This can be calculated with the driving time, driving speed and energy consumption per km . An example is given in section VI.

The minimum amount of energy that need to be charged in one time slot j before the end of stop-over k should require the following inequality

$$SOC_0 + \sum_{j=1}^n \sum_{k=1}^r E_{j,k} \geq SOC_{Min} + \sum_{j=1}^n \sum_{k=1}^r E_{drivej,k}, \quad (4)$$

where SOC_{Min} means the lowest allowed SOC of EV battery, denotes Min , r is the r th stop-over during each time slot j .

The stop-over inequality constraints A_t is a lower triangular unit matrix and the dimensions of matrix A_t can be deduced from the time slot j and stop-over index k .

From inequality formula 4, it follows that

$$B_e = \begin{bmatrix} \{-E_0 + Min + E_{drive1,1}\}, \dots, \\ \{-E_0 + Min + E_{drive1,1} + \dots + E_{drive1,m_1}\}, \dots, \\ \{-E_0 + Min + E_{drive1,1} + \dots + E_{drive1,m_1} + \dots + \\ E_{driveN,1}\}, \dots, \{-E_0 + Min + E_{drive1,1} + \dots + \\ E_{driveN,1} + \dots + E_{driveN,m_N}\} \end{bmatrix}^T \quad (5)$$

Let the maximum amount charged energy in each stop-over k during slot j be

$$SOC_0 + \sum_{j=1}^n \sum_{k=1}^r E_{j,k} \leq \left\{ wE_{cap} + \sum_{j=1}^n \sum_{k=1}^r E_{drivej,k-1} \right\}, \quad (6)$$

where w is the parameter which express that the charging behavior of the battery is a linear process.

Thus, one can get

$$B_b = \begin{bmatrix} \{wE_{cap} - E_0\}, \dots, \\ \{wE_{cap} - E_0 + E_{drive1,1} \dots + E_{drive1,m_1-1}\}, \dots, \\ \{wE_{cap} - E_0 + E_{drive1,1} \dots + E_{drive1,m_1-1} \dots + \\ E_{driveN,1}\}, \dots, \{wE_{cap} - E_0 + E_{drive1,1} \dots + \\ E_{drive1,m_1} \dots + E_{driveN,1} \dots + E_{driveN,m_N-1}\} \end{bmatrix}^T \quad (7)$$

In reality, it is reasonable to assume that users expect the EV battery at a certain status in a specific time. This can be illustrated by the following equation:

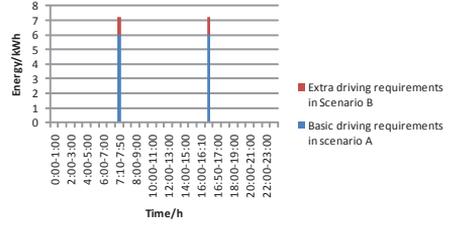


Fig. 2. Driving requirements $E_{drivej,k}$ for EV 1

$$\sum_{j=1}^n \sum_{k=1}^r E_{j,k} + SOC_0 - \sum_{j=1}^n \sum_{k=1}^r E_{drivej,k} \geq SOC_{set} \quad (8)$$

Because the charging power ability is constant, we let $E_{max} = P * t_{stopj,k}$.

IV. EXTENSION TO A LARGE SCALE OF EV FLEET

Since the model is suitable for each vehicle, and if matrix of A_t is noted by $A_{j,k}$ in formula (1), i is introduced to denote the index of EV, $1, 2, \dots, i, \dots, M$, then the extendable model of EV fleet can be given by following formula:

$$\begin{pmatrix} -A_{1,j,k} \\ -A_{2,j,k} \\ \vdots \\ -A_{M,j,k} \end{pmatrix} \quad (9)$$

The same approach is also used for other parameters B_e, B_b . In this way, the charging schedule for each EV can be obtained. For individual EVs, the charging schedule may include two or more charged energy sections in one time slot. With the purpose of calculating the whole charged energy/power in one time slot, we will sum those time slots in which they contain two or more charged energy section for each individual EV:

$$E_{i,j} = \sum_{k=1}^{m_j} E_{i,j,k} \quad (10)$$

We can then get the charging schedule of the EV fleet by the sum of each EV corresponding to each time slot, which can be expressed by the following equation:

$$E_j = \sum_{i=1}^M E_{i,j}. \quad (11)$$

V. RESULTS

In this section, we give examples to demonstrate the effectiveness of the proposed methods with two scenarios. In scenario A, two cases are studied with the goal of minimizing the charging cost. In order to manage the uncertainty of the driving pattern, a certain amount of driving requirements are added for each $E_{drivej,k}$ in scenario B. Besides this,

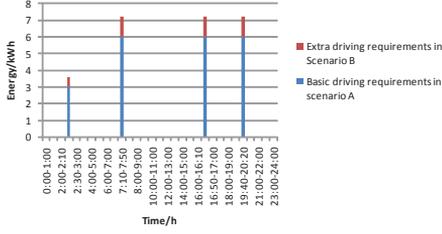


Fig. 3. Driving requirements $E_{drive_{j,k}}$ for EV 2

the optimal charging results concerning the user's special preference are also studied. In addition, longer time horizons are introduced for planning charging with the purpose of getting more optimal results. All three studies in scenario B are in terms of other factors.

A. Optimal Charging Schedule With Basic Driving Requirements

This scenario presents the case studies with basic driving requirements. The plan duration is 24 hours and the time slot is set to 1h. We expect to use the representative driving patterns of EVs in Denmark to test and illustrate this methods, however, this kind of driving pattern are not available at this moment. But, we are in the process of generating this driving pattern from the GPS survey data on vehicle fleets (December 2001-April 2003) provided by Department of Transport, Technical University of Denmark. Meanwhile, this paper focus on the methods to generate the charging schedule for an EV fleet, therefore, some artificial driving requirements and assumptions are given in the following:

- Based on the study [13], $150Wh/km$ is used to calculate the energy consumption from the driving distance.
- The drive speed is constant for all EVs, e.g. $60km/h$.
- Power capacity of Battery is $20kWh$, i.e. E_{cap} and the charging power is $2.3kW$ based on $10A * 230V$.
- State of charge (SOC) should be between 20% and 85% E_{cap} , because the battery life can be longer if the SOC is large than or equal to 20% and the charging behavior will be close to linear equation when the SOC is below 85%.

Two individual cases EV 1 and EV 2 are considered based on the above assumptions, representing the normal and complicated case, respectively. In Fig. 2 and Fig. 3, we give the driving requirements for these two EVs with the light blue block. Fig. 4 presents the spot price in one day (blue curve) (12, Jan, 2011), DK-West, from NordPool, which is used for the predicted price for fleet operator.

The initial energy state E_0 is set $4kWh$, $4kWh$ for EV 1 and EV 2, respectively. In Fig. 5 and Fig. 6, the charging schedule for EV 1 and EV 2 are given. It is clear that the charging time is located during the time slots where the electricity price is lower compared to other time slots while still fulfilling the driving needs.

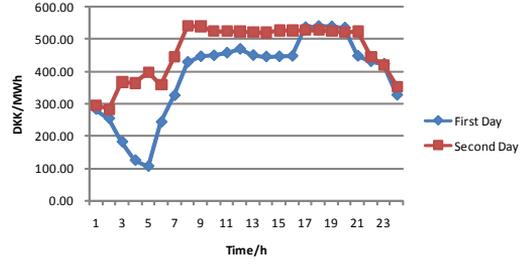


Fig. 4. Two days Spot price

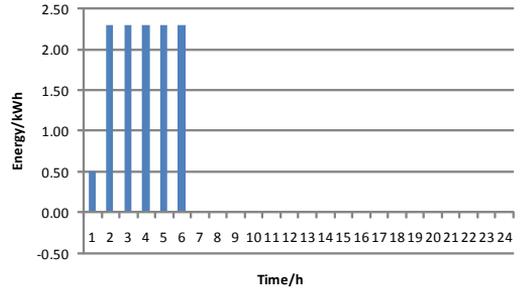


Fig. 5. Charging schedule of EV1 in scenario A

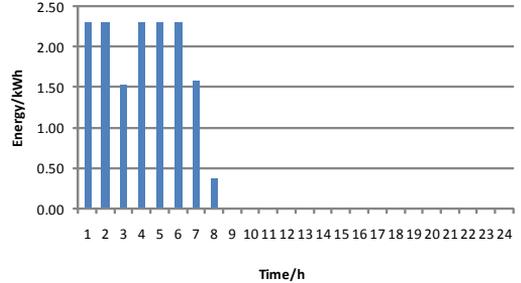


Fig. 6. Charging schedule of EV2 in scenario A

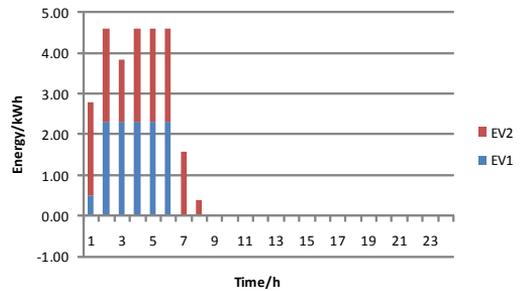


Fig. 7. Charging schedule of EV fleet in scenario A

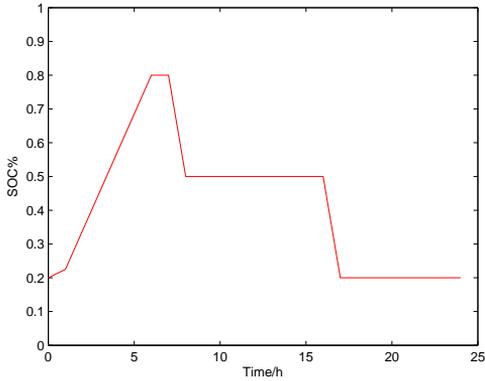


Fig. 8. State of Charge of EV1 in scenario A

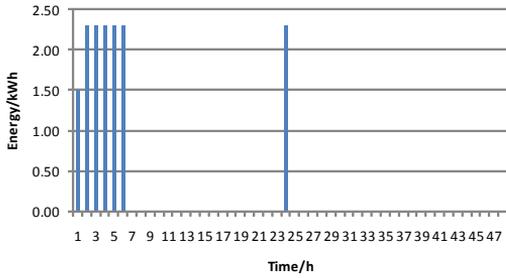


Fig. 9. Charging schedule of EV1 within longer plan duration in scenario B

B. Optimal Charging Schedule With other Factors

The question in this mathematical model is that this will always result in minimum SOC at the end of the plan duration, which can be shown by the fig. 8. In order to manage it, the extended plan duration is introduced here. By taking advantage of more decision variables, more optimal results can be obtained. One question remains: how long should the plan duration be? This relies on the prediction of the spot price. If the more accurately predicted spot price is available for this longer plan duration, the fleet operator can benefit from such solution. However, the fleet operator might lose more if there are large deviations between forecasted and the real price. An example with a two-days time duration is studied here, Fig. 4 shows continuous two-day electricity spot price, (12-13, Jan, 2011), DK-West. The charging schedule is shown in Fig. 9, in which the last hour of the first day is also charged for next day. With this method, the day-ahead charging schedule can be iteratively calculated.

In addition, the above scenario has limitations when the users might want to change their driving requirements, e.g., need more energy than predicted $E_{drivej,k}$. Therefore, with

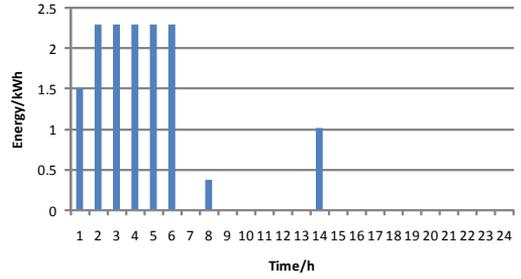


Fig. 10. Charging schedule of EV1 with more driving requirements in scenario B

the purpose of managing the uncertainty of user's driving requirements, it is reasonable to add a certain amount driving requirements for the predicted $E_{drivej,k}$. But how many driving requirements should be added? This question should rely on two main aspects, charging costs and the possibilities of managing uncertainties of driving requirements. In other words, the charging costs can be lower with the more accurately predicted driving requirements. We do not give such data analysis since the real driving pattern is not available now. One case is given to show the difference, this can be illustrated in Fig 2 and Fig 3 with the red block on the top of the light blue block, which here 20% more driving requirements are added for each $E_{drivej,k}$. The corresponding charging schedule is shown by Fig 10.

Besides the above conditions, some users might have special preferences, e.g., they want to ensure their EVs are close to be fully charged in the morning since they can have more flexible choices. If we assume the users in Scenario A are risk takers, then the users in this Scenario are more focus on the reliability. However, how far the SOC of the battery should be charged? This is the similar problem compared to the above one. Also, we give an example, based on the normal case EV1 with the light blue in Fig. 2 driving requirements. We assume that this user want his/her EV to be charged to SOC 85% at 7:00 AM. Fig. 11. illustrates the charging schedule.

The above case studies only gave examples of an EV fleet with two EVs and Fig. 7 illustrates the result of EV fleet charging schedule. This is indeed a small number. Fig. 12, which is obtained from ongoing project named Edison [18], can illustrate the aggregation management of the EV fleet by fleet operator. Meanwhile, this picture also show the potential importance of the fleet operator, since a large scale EV fleet need to be managed which can optimally use the batteries to balance the intermittency of wind. We think the above work can give a method for the fleet operator to obtain the optimal charging schedule for the whole EV fleet.

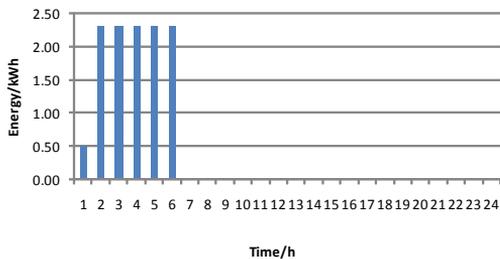


Fig. 11. Charging schedule of EV1 with user's special preference in scenario B

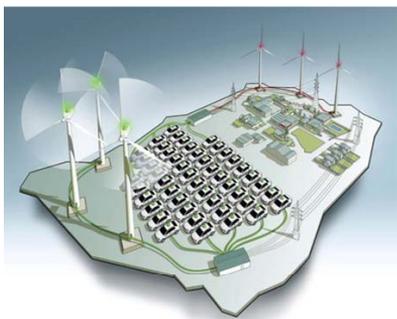


Fig. 12. Demo aggregating EV fleet

VI. DISCUSSION AND CONCLUSIONS

This paper presents a theoretical framework for designing and analysis of an EV fleet optimal charging schedule. The model reveals a general charging process for individual EVs to get their charging schedules with the criteria of obtaining a minimum charging cost. By formulating this problems via linear models under a certain assumptions, this model for optimal charging can adapt to any driving pattern with flexible time intervals (from hour to minutes).

Future research is planned to be done from the following perspectives:

1. Analyze the given 'Danish National Transport Survey data' and present a representative driving pattern, and this driving pattern will be used in the analysis of EV optimal charging.

2. Extension the EV fleet charging schedule with intra-day markets, regulating power markets. With the intra-day markets and regulating power markets, the EV aggregator can dynamically evaluate the day-ahead charging schedule and obtain the optimal potential profits after day-ahead market. This research can also be extended to a real time market.

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currently undertaken at the Center for Electric Technology, Technical University of Denmark and partner contributors within the program, which aims to utilize the EV as balancing resources to support the long term goal of integrating 50% wind power capacity [5][18]. The authors also would like to give thanks to Anders Bro Pedersen for his comments.

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A.3 Optimal control of an electric vehicle's charging schedule under electricity markets

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Optimal control of an electric vehicle's charging schedule under electricity markets

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Abstract As increasing numbers of electric vehicles (EVs) enter into the society, the charging behavior of EVs has got lots of attention due to its economical difference within the electricity market. The charging cost for EVs generally differ from each other in choosing the charging time interval (hourly), since the hourly electricity prices are different in the market. In this paper, the problem is formulated into an optimal control one and solved by dynamic programming. Optimization aims to find the economically optimal charging solution for each vehicle. In this paper, a nonlinear battery model is characterized and presented, and a given future electricity prices is assumed and utilized. Simulation results indicate that daily charging cost is reduced by smart charging.

Keywords Optimal control · Dynamic programming · Nonlinear control · Electric vehicles

1 Introduction

An important solution to curb CO₂ emission and oil dependency taken by the automobile industry is the introduction of

electric vehicles (EVs) [1, 2], since the EVs can shift petroleum consumption to electricity. As an asset, it is well understood that the EV can provide valuable service to power systems, more than its transportation function. On the one hand, battery of the EV can be considered as a controllable load. With optimal charging or smart charging for the battery, the peak load can be shaved, and by doing this, EV owners could maximize their profits by purchasing energy at the possibly lowest electricity price. On the other hand, battery of the EV can also be seen as energy storage equipment which has possibility to provide vehicle-to-grid (V2G) and grid-to-vehicle service and thereby earning profit [3–6]. Therefore, an optimal charging scheme is required to coordinate the needs from the power system and maximize the EV owner's profit. In a general word, for a power system operator, "optimal" can be interpreted as enable the large penetration of renewable and distributed energy resources, like wind power, photovoltaics, and also accommodate the new loads, like EV and heat pump, both reliably; from EV users perspective, optimal means minimizing their charging cost without interfering their daily drive profile.

Many researches have been done on EV optimal charging management. In the early 1980s, Heydt has already researched the impact of electric vehicles on the grid and concluded that typical driving patterns will likely to coincide the charging with peak load periods of power system [7]. So, methods are developed to avoid overloading with off-peak charging. In paper [8], Kristien researches the impact of charging PHEVs on a residential distribution grid, investigates the difference between coordinated and uncoordinated charging with respect to various penetrations of PHEVs. Olle presents a linear approximation-based method to formulate and coordinate the optimal charging problems, grid constraints in terms of thermal overloading are considered. With this method, the flexible charging ability of EVs is utilized to

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mitigate the grid overloading problem; and with this charging flexibility, individual EV owner's can be controlled to charge at the period with the lower electricity price [9]. In paper [10], Niklas proposes two dynamic programming-based algorithms to find the economically optimal solution for vehicle owner. The first reduces daily electricity cost substantially. The latter takes into account vehicle-to-grid support as a means of generating additional profits by participating in ancillary service markets. Sekyung proposes an aggregator that makes efficient use of the distributed power of electric vehicles to produce the desired grid scale power, which is V2G concept that can make revenue from providing regulation service [3].

Typically, an optimal control problem includes a cost function of state and control variables and the control objective is to find the paths of the control variables that minimize the cost functions. In the scope of smart charging of EVs, the cost function can be derived from two perspectives: one is the single charging cost of EV without grid constraint, which means the grid is large to handle the new load of EVs. Another optimal control problem is to minimize the total monetary cost of fulfilling the charging requirement, given assume spot price and monetary price for overloading phenomenon. In this paper, we take the first option and consider the EV as a controllable load, and investigate its smart charging potential. The functionality of regulation service will not be discussed here.

The following paper is organized as follows. A nonlinear model of electric vehicle is modeled in Sect. 2. Section 3 gives a system architecture with appropriate assumptions. Section 4 constructs a dynamic programming-based mathematical model. In Sect. 5, one case is studied to investigate the optimization of EV charging cost.

2 Electric vehicle model

With the purpose of charging planning, the EVs are considered to be battery packs in this study that have nonlinear behavior [9]. Each battery is modeled as a steady-state equivalent circuit, which represented by an ideal voltage source V_{oc} in series with an internal resistance R_{int} .

Both the voltage source and the internal resistance are dependent on the state of charge (SOC) of the battery. Based on the equivalent circuit, we have the following two equations to describe it.

$$U_2 = V_{oc} - R_{int} \cdot I_2 \tag{1}$$

and

$$P_2 = U_2 \cdot I_2 \tag{2}$$

Equations (1) and (2) above are combined with Ohm's law to find the current, which is a function of the SOC, V_{oc} , and

power P_2 (negative during charging) to the battery. Two solutions are mathematically possible, but only the smaller one is physical because battery terminal voltage is limited to a certain range around that of the open circuit [10].

$$I_2(\text{SOC}, P_2) = \frac{V_{oc}(\text{SOC}) - \sqrt{(V_{oc}(\text{SOC}))^2 - 4 \cdot R_{int}(\text{SOC}) \cdot P_2}}{2R_{int}(\text{SOC})} \tag{3}$$

In order to study the optimization charging planning for EV battery, a battery cell is given in this paper. The battery parameters depend on the information of certain cell characteristics and the size of the battery pack, which are shown in Fig. 1 and Table 1, including the datasheet parameters for the Saft VL 45E [18]. This type of model is commonly used when researching the optimal control of EVs. E_{int0} and Q_0 represent the maximum energy storage and total capacity of the battery cell, respectively. Other parameters V_{oc} , R_{int} , and so on have been defined using the model of above equations and using information on the datasheet. The equivalent resistance R_{int} is approximately constant for the majority of the charge cycle. Therefore, in this paper, it is modeled as a constant resistance.

The battery pack for electric vehicle is scaled according to the scaling equations in Table 1. Note that the scaling variables n_s and n_p are not necessarily integers. Consequently, the resulting battery pack after scaling may not be implementable in a vehicle. It is however assumed that the behavior of the pack reflects the real behavior sufficiently well.

3 System architecture and assumptions

In general, two kinds of control architecture can be deployed for the optimal charging of EVs, one is called centralized control and the another is named decentralized

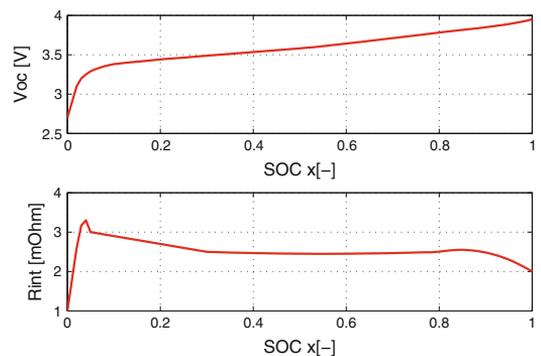


Fig. 1 The open circuit voltage and internal resistance of the Saft VL 45E cell

Table 1 Parameters of the VL 45E cell

Variable	VL 45E	Unit	Scaling
E_{int0}	590.4	kJ	$E_{int0} \cdot n_p \cdot n_s$
Q_0	45	Ah	$Q_0 \cdot n_p$
V_{max}	4	V	$V_{max} \cdot n_s$
V_{min}	2.7	V	$V_{min} \cdot n_s$
I_{max}	100	A	$I_{max} \cdot n_p$
V_{oc}	See Fig. 1	V	$V_{oc} \cdot n_s$
R_{int}	See Fig. 1	ohm	$R_{int} \cdot \frac{n_s}{n_p}$

control, the main difference lies in the deployment of the controller in different position. For the centralized control, the controller is put on the aggregator level, and for the decentralized control, the controller is located at the individual EV level. Both of the centralized and decentralized controls have its advantages and disadvantages. For centralized control, the aggregator can aggregate large population of EVs and then have more competence in the electricity market, for example, may have the chance to buy cheaper electricity, provide ancillary service to grid more stable. However, the system operator would require significant communication ability with EVs and powerful computation capability. While decentralized control can release the highly requirement on communication, but the drawback is that the individual EV needs to collect and store trip history and that, if EVs need to consider their charging schedule with grid constraints, the need for communication will be high.

Consider the needs of an optimal control study, centralized control architecture is presumed, in which a single entity (aggregator) directly controls the charging strategy of every vehicle to facilitate smart charging [11], and each vehicle indirectly accesses to electricity market through this aggregator, which is a smart interface between EV fleets and market to play a role of coordinating charge and discharging operation of multiple vehicles. With this centralized control, there exists an underlying assumption, that is, the existence of contracts between aggregator and consumers, which enable the aggregator send explicit control signal to charge or discharge the EVs. The general information flow is depicted below:

Figure 2 shows that aggregator is fed with following data for charging plan making: predicted electricity price, future driving pattern, grid constraints, and EV data, such as EV model and state of charge of EV battery. If Evs implemented in a large scale, peak load increases significantly and grid may be destabilized. In this case, grid constraints are essential for aggregator. In our study, however, only one vehicle’s charging schedule is researched, which means grid constraints could be neglect. With

all of these information, the aggregator can make an optimal control strategy for EV.

In order to achieve these centralized control, some assumptions are given and listed below:

- The aggregator is set up to be a price taker, which means the aggregator does not have a sufficiently large market share to affect electricity price.
- The electricity price is assumed to be known by the aggregator, while in the reality, the aggregator needs to predict the electricity spot price.
- An automated communication technology is exist to enable the smart charging, that is, all information of EVs can be immediately communicated to aggregator, and the control signal generated by the aggregator can be delivered to EVs.
- In order to have a successful charging plan, a representative driving pattern is essential. Normally, intra city or short-term driving patterns are largely predictable due to fixed working hours and fixed business schedules and routes. Therefore, a future driving pattern is assumed to be obtained by estimating data of past trips or established driving plans. Moreover, electricity demand of every trip is also needed to be assumed based upon driving pattern.

4 Control task formulation

The following notation will be used throughout this paper. Since the market with day-ahead pricing is assumed, the charging plan covers an entire day. For this short-term planning, the time horizon $[0, N]$ of a day is discretized into equidistant time intervals $[k, k + 1]$ with $k = 0, \dots, N - 1$. It is assumed that the time interval is Δt .

This problem is addressed by considering the following discrete system which describes the battery:

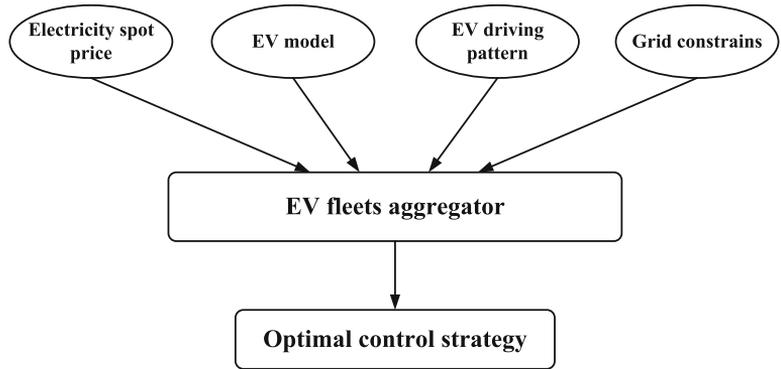
$$x_{k+1} = T(x_k, u_k, k) \tag{4}$$

State variable x_k represents the state of charge (SOC) of the battery at time k . x_k is not only discrete in time (index k) but also in value. Any value has to be included in the predefined set X , which can be calculated by a function of charge Q_k and total capacity Q_{max} .

$$x_k = \frac{Q_k}{Q_{max}} \tag{5}$$

u_k in Eq. (4) is the control variable, which is dimensionless and discrete. P_k is the charge power when plug-in. In order to obtain P_k , u_k is multiplied with the maximum available charge power ($P_{max-plug}$) when plug-in. The electric vehicle discussed in this paper is purely electric propulsion system, which is characterized by an electric energy conversion

Fig. 2 Information flow in centralized control



chain upstream of the drive train, roughly consisting of a battery (or another electricity storage system) and an electric motor with its controller [12]. EV does not have an internal combustion engine to provide power for propulsion. Battery must be charged from an external electric network. Due to this fact, the values of u_k are fixed at 0 when driving, while these values range from 0 to 1 when plug-in. If U_{plug} is set that covers all possible values of u_k , its discretization may be described as follows:

$$u_k = \begin{cases} u_k \in U_{\text{plug}}, & k \in K_{\text{plug}} \\ u_k = 0, & k \in K_{\text{driv}} \end{cases} \quad (6)$$

K_{plug} is a set of indices k within the time periods when the vehicle is plugged in, while K_{driv} refers to the driving intervals. The summation of the number of elements in K_{plug} and K_{driv} is N , which denotes the total number of time intervals. Any index k in K_{plug} or K_{driv} has to be element of the predefined set K .

$$k \in K = \{K_{\text{plug}}, K_{\text{driv}}\} \quad (7)$$

A specific control strategy is denoted by

$$u = \{u_0, u_1, u_2, \dots, u_{N-1}\} \quad (8)$$

Any value of u_k has to be element of a predefined set U , which known as set of admissible decision. The total cost of a sequence, f_0^U , is given by the cost of the final step, $f_N(x_N)$, plus the cost for all other steps, $v_k(x_k, u_k, k)$, then we have:

$$f_0^U(x_0) = f_N(x_N) + \sum_{k=1}^{N-1} v_k(x_k, u_k, k) \quad (9)$$

To minimize the objective function (4.9), the optimal control strategy $u^* = \{u_0^*, u_1^*, u_2^*, \dots, u_{N-1}^*\}$ has to be obtained. This is a classic dynamic programming formulation and can be solved as described by the literature [13, 14, 19]. The optimal trajectory is calculated starting with the cost of the last step and going backwards through time until the first state's optimal cost $f_0^*(x_0)$ is given by the algorithm. The recursive equation is listed as follows:

$$f_k(x_k, u_k) = \min\{v_k(x_k, u_k) + f_{k+1}(x_{k+1})\} = \min\{v_k(x_k, u_k) + f_{k+1}(T(x_k, u_k, k))\} \quad (10)$$

$$u_k^* = \operatorname{argmin}(f_k(x_k, u_k)) \quad (11)$$

According to dynamic programming, some special terms are given as follows:

- k : step
- X : set of admissible state
- U : set of admissible decision

Admissible state set X must be defined appropriately, because $T(x_k, u_k, k)$ may not be any of the elements of X where f_{k+1} is know if set X is not defined good enough, which means $T(x_k, u_k, k)$ may not equal with x_{k+1} as described in Eq. (4). Actually in practice operation, errors are hardly avoided that $T(x_k, u_k, k)$ will usually not be on a grid point no matter how the set X is defined. Therefore, an approximation is needed. Normally, x_{k+1} is defined as a range by plus a margin of 10 % to cover the possible $T(x_k, u_k, k)$.

4.1 Cost of final step

The objective function is to ensure that the battery is fully charged before the first trip of the following morning. Step N is the moment right before the next day's departure. Therefore, the value of x_N is 100 %, and no charging operation happens at step N . The cost of final step $f_N(x_N)$ should be defined as.

$$f_N(x_N) = 0 \quad (12)$$

4.2 Cost of other step

For EV, a purely electric propulsion system, it is important to acknowledge different step function v_k for driving mode and plug-in charging mode. The most general case is given by introducing the following discontinuity:

$$v_k(x_k, u_k, k) = \begin{cases} v_{\text{plug}}(x_k, u_k, k), & k \in K_{\text{plug}} \\ v_{\text{driv}}(k), & k \in K_{\text{driv}} \end{cases} \quad (13)$$

where

$$v_{\text{plug}}(x_k, u_k, k) = \eta_k \cdot u_k \cdot P_{\text{max-plug}} \cdot C_{\text{el}}(k) \cdot \Delta t \quad (14)$$

and

$$v_{\text{driv}}(k) = 0 \quad (15)$$

η_k denotes the efficiency parameter between step k and $k + 1$. C_{el} is the price of electricity per unit of energy. Δt is the time interval between step k and $k + 1$. Since EV is a purely electric propulsion system, charging cannot take place during driving period as hybrid electric vehicle did, and the charging cost is set to 0.

4.3 Equation of state transition

In order to well describe battery charging, a first-order system is developed with Backward Euler method applied to Eq. (5), where x_k is an actual SOC at the step k , x_{k+1} is a desired SOC at step $k + 1$.

$$\begin{aligned} x_{k+1} &= T(x_k, u_k, k) = x_k + \Delta t \cdot \dot{x}_{k+1} \\ &= x_k + \Delta t \cdot \frac{\dot{Q}_k}{Q_{\text{max}}} \\ &= x_k + \Delta t \cdot \frac{I_2(x_k, k)}{Q_{\text{max}}} \end{aligned}$$

where

$$I_2(x_k, k) = \frac{V_{\text{oc}}(x_k) - \sqrt{(V_{\text{oc}}(x_k))^2 - 4 \cdot R_{\text{int}} \cdot \frac{P_{\text{BT}}(k)}{n_s}}}{2R_{\text{int}}} \quad (16)$$

that comes from Eq. (3) given in Sect. 2. The battery current is calculated using

$$P_{\text{BT}} = n_s \cdot U_2 \cdot I_2 \quad (17)$$

and

$$P_{\text{BT}}(k) = \begin{cases} -\eta_k \cdot u_k \cdot P_{\text{max-plug}}, & k \in K_{\text{plug}} \\ P_{\text{dr}}, & k \in K_{\text{driv}} \end{cases} \quad (18)$$

Equations (17) and (18) are deduced based on Sect. 2 EVs are considered to be battery packs in this study, which is implied with a parallel wiring, resulting in an equal power contribution of all cells. $P_{\text{dr}}(k)$ denotes power requirement during driving cycle. It is obvious that power requirement of every step when driving is hardly predicted. Instead, it is possible to predict energy requirement throughout a whole driving trip, which can be a replacement of power requirement. Note that the relation shown in Eq. (17) is only exact for infinitesimal time intervals. To achieve sufficient accuracy, time interval choosing is very important. It should be done in a way that maximum charge $\Delta t \cdot I_2$

is small enough and does not influence the results of the battery equations substantially.

These state transition models [Eq. (16)] are general enough to account for the possibility of parallel processing among the various control strategies, as well as for redundancy in the database. Once the concept of state transition has been properly defined, dynamic programming can be used to find the state containing the answer to the query that has the minimum cost and to find the optimal trajectory to that state (i.e., optimal sequence of processing operations) [15].

5 Case study

In this section, a case is studied and the goal of optimization is to present a charging schedule for every individual vehicle to minimize the cost of electricity while satisfying the vehicle owner's requirements. In this case, vehicle would be plugged in every time when the driving finished. A comparison is made between the results of an EV with a fast charging scheme and those of the dynamic programming-based method.

The charging schedule is divided into time intervals for a 24-h-based period. The period starts from the first second when the vehicle owners begin their first trip and ends right before the next day's departure, which has 288 intervals of 5-min each. As mentioned previously, the objective function is to ensure that the battery is fully charged before the first trip of the following morning, which means $x_0 = 100\%$ and $x_N = 100\%$. The vehicle used to study in this paper is a battery packs, which is a purely electricity propulsion system. The basic battery information is shown in Sect. 2, and more additional is listed in Table 2. U is defined as the set of admissible state which indicate the possible control signals and contains 11 elements which limited in $[0, 0.1, 0.2, \dots, 1.0]$. X is defined as the set of admissible decision which indicate the possible SOC of the battery and contains 101 elements which limited in $[0, 1, 2, \dots, 99, 100\%]$. Δt is time interval, which is defined as 5 minutes. Here, we give $n_s = 100$ and $n_p = 1.12$. Typically, the battery operation is limited to a given state of charge operating range. It is assume that battery has a minimum state of charge of 10%. Hence, here the SOC is limited between 10 and 100%. Moreover, it is important to know a driving behavior of a vehicle, which includes the departure time, return time, and energy requirements of every trip. Based on the vehicle parameters, a driving map includes three trips during a day is given in Table 3.

Another important piece of information is electricity prices, which are based upon a typical work day of 04.05.2011 from Nordpool Spot market area Denmark West [17]. To obtain an optimal charging schedule, a price

Table 2 Simulation parameters

Discretization	Parameters
U	11
X	101
Δt	300 s
Battery	Value
Total capacity	50 Ah
Maximum energy storage	18.4 KWh
Maximum plug power	4 KW
R_{int}	0.0025 ohm

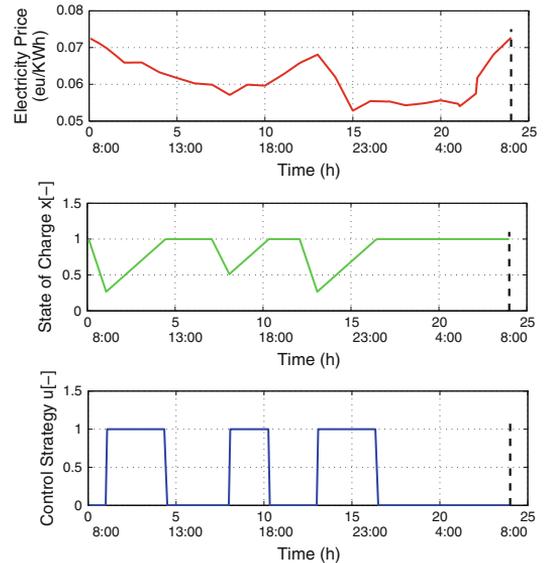
Table 3 Driving behavior

Trip	Departure time	Return time	Energy requirement (KWh)
1	8:00	9:00	11.04
2	15:00	16:00	13.25
3	20:00	21:00	11.04

for electricity service is prerequisite. Any optimization should take use of real prices of one day.

5.1 Fast charging

Fast charging is a kind of uncoordinated charging. It assumes that vehicles owners face a flat price throughout the whole and consequently their vehicles are charged instantaneously when they are plugged in, and the batteries will be fully recharged as fast as possible without considering the daily electricity price. Some vehicle manufacturers, such as Nissan, give their own definition for battery fast charging. For example, Nissan LEAF's battery is intended to accept several rapid charging scenarios including a 50 KW "fast charge" which gives 80 % charge in thirty minutes, or a five-minute fast charge which delivers an additional 31 miles of range. These rapid recharge modes will require a special three-phase charger, which is most likely to be owned by commercial or governmental entities in distributed charging stations [16]. This fast charging offers most flexibility to driver. However, it is not the fast charging we discussed here, because homeowners do not have a spare 50 KW charging power, but prefer to have a common, single-phase 220 V with maximum 4 KW charging power. The profiles with fast charging are given by Fig. 3. It is obvious that every time when the vehicle finishes a trip, the battery will be charged immediately without considering the electricity prices. The battery is fully charged as fast as possible once it is plugged in. The fast charging strategy provides customers with flexibility; however, the electricity costs will be high, which for the profiles amount to EU 2.2415.

**Fig. 3** Profile with fast charging

5.2 Smart charging

The idea of the smart charging is to achieve optimal charging to minimize the charging cost. The results of the fast charging algorithm is compared to an EV with a dynamic programming-based smart charging scheme. With the automated communication technology, all information can be immediately communicated to aggregator, which then returns a charging plan for an individual EV for the following day. The optimal control strategy will be obtained and sent to the individual vehicle as control signals for charging power. It is expected that most of charging occurs when given the comparably lower prices. The results of the dynamic programming-based method are shown in Fig. 4. The simulation parameters are given in Table 2.

From Fig. 4, we have a general idea that electric vehicle charging is done when the price for electricity is lowest. The SOC of battery shows that the battery does not have to be fully charged before next trip. Instead, it would be sufficient if the SOC is charged enough to support the energy consumption for the next trip. This leads to a electricity cost of EU 1.8333 for a whole day, which is cheaper than the fast charging cost. Smart charging cannot offer flexibility for driver as fast charging does. Consequently, sometimes when drivers drive away their vehicles before the preannounced departure time, the battery may not be enough charged to meet the energy requirement for the next trip, which the drivers have to accept. It is also interesting that when the vehicle is charged, it always does

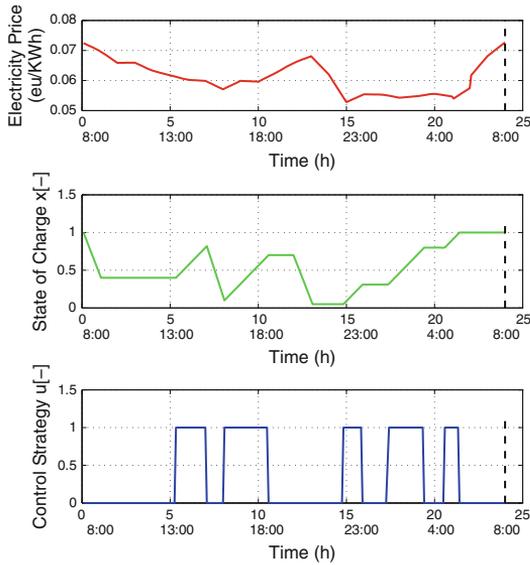


Fig. 4 Profile with smart charging

its charging with the maximum available power, which means u_k is equal to 1 when x_k is increasing. This is caused by the fact that intraday price differences are higher than loss costs and supported by increased inverter efficiency at high power throughputs [10]. Due to this consideration, some paper studies on control of charging sequence with charging rate fixed to the maximum, instead of charging rate control, such as [3].

5.3 Comparison for the simulation results

The code for smart charging optimizes a 24-h interval in Matlab takes 13.19 s on 2.1-GHz CPU with 1.99 GB of RAM.

The following Table 4 gives a comparison between two charging algorithms. Each has both advantages and disadvantages as can be seen from the table. However, it is widely recognized that electric vehicle will be a controllable load in the near future, which is more intelligent and has more communication ability, even though giving a smart charging schedule takes more time due to complicated charging control algorithm.

6 Conclusions

This paper presents a mathematical formulation and a dynamic programming-based algorithm for optimizing an EV’s charging schedule with given electricity prices and driving pattern within a centralized control architecture.

Table 4 Comparison between fast and smart charging

Charging algorithms	Advantages
Fast charging	More flexibility, Fast computing time
Smart charging	Low charging cost, More intelligent, controllable, More communication ability
Charging algorithms	Disadvantages
Fast charging	High charging cost, Less intelligent, uncontrollable, Less communication ability
Smart charging	Less flexibility Comparably slow computing time

Smart charging without provision of regulation service reduces daily electricity costs for driving from EU 2.2415 to EU 1.8333 compare with fast charging. With smart charging, EV is recharged during the lowest electricity price period, where is also the off-peak hours. It naturally drops the possibility of grid overload during the peak load hours.

More work could be done in the future. Only one electric vehicle’s charging schedule has been researched here. Studies of optimal control on large number of EVs should be done, which involves high requirement on communication, and possibility that EV charging may impact the electricity price. Therefore, decentralized control architecture can be considered and electricity price forecasting models should be properly developed. Furthermore, the optimization model should be extended to account for providing of regulation service and given different type of electric-drive vehicles as well as various driving patterns.

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A.4 Numerical comparison of optimal charging schemes for electric vehicles

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Numerical Comparison of Optimal Charging Schemes for Electric Vehicles

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Abstract— The optimal charging schemes for Electric vehicles (EV) generally differ from each other in the choice of charging periods and the possibility of performing vehicle-to-grid (V2G), and have different impacts on EV economics. Regarding these variations, this paper presents a numerical comparison of four different charging schemes, namely night charging, night charging with V2G, 24 hour charging and 24 hour charging with V2G, on the basis of real driving data and electricity price of Denmark in 2003. For all schemes, optimal charging plans with 5 minute resolution are derived through the solving of a mixed integer programming problem which aims to minimize the charging cost and meanwhile takes into account the users' driving needs and the practical limitations of the EV battery. In the post processing stage, the rainflow counting algorithm is implemented to assess the lifetime usage of a lithium-ion EV battery for the four charging schemes. The night charging scheme is found to be the cheapest solution after conducting an annual cost comparison.

Index Terms—Electric vehicle, mixed integer programming, optimal charging, rainflow counting, vehicle-to-grid, V2G

I. INTRODUCTION

THE technique of optimal charging in the context of deregulated electricity markets, sometimes referred as smart charging, has recently caught a lot of attention, as there is a tremendously growing need for electrifying the transportation sector [1]. The term “optimal” can be generally interpreted from two perspectives: the EV owners and the power system operators.

From the EV owners' point of view, “optimal” can be simply interpreted as minimizing the cost of charging while guaranteeing their need for driving. In [2]–[5], this perspective has been intensively investigated based on various modeling techniques including linear programming, dynamic programming and quadratic programming. A common impression inferred by these studies is that the optimal charging as a feasibility solution can considerably reduce the cost of charging; however, to support a large-scale roll-out of EV, services like V2G have to be offered by EV or EV fleet to improve the EV economy [6]–[7].

From the power system operators' point of view, “optimal” can be generally interpreted as a complex objective which aims to maximize the advantages of EV and minimizes its

disadvantages. The energy storage nature of EV makes it a potential solution to many power system problems, such as load shifting and frequency regulation. Meanwhile, its nature of being a mobile electrical load challenges the power system operation, as an inappropriate integration could easily cause voltage issues and overloading in the distribution network. Regarding this aspect, intensive studies have been done in [8]–[11], wherein coordinated charging schemes for an EV fleet with either centralized or decentralized control structures are developed to handle grid constraints and meet the driving requirements at the same time.

Apart from the different perspectives of the two groups of stakeholders, the optimal charging schemes are also heavily dependent on a large number of factors, including:

- 1) range of uncertainty related to electricity price and driving pattern [12];
- 2) fidelity of the EV battery models which varies from linear to non-linear;
- 3) modeling approaches used to describe the charging process and the associated optimization techniques which span from the conventional linear programming to the genetic algorithms [13];
- 4) time resolution used in the various simulations that spans from a few minutes up to hours;

and so on.

In this study, four different optimal charging schemes for EV, namely night charging, night charging with V2G, 24 hour charging and 24 hour charging with V2G, are formulated as a set of mixed integer programming problems. Based on the practical driving data and electricity prices collected for Denmark in 2003, these charging schemes are simulated at a time resolution of 5 minute. Objectives for the four charging schemes are set to charging cost minimization, due to the fact that today's EV penetration is relatively low compared to the other Distributed Energy Resources (DER) technologies and some distribution grids can handle the penetration level up to 20% [14]. In the following text, the mathematical formulation for various optimal charging schemes is described in Section II. Section III presents the numerical model development. Results and discussions are summarized in Section IV, wherein battery life and annual cost comparison among the four schemes are included. Section V concludes the study.

II. PROBLEM FORMULATION

Today, energy procurement of EVs into the power

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system is very market-driven, given the fact that the economy of EVs can be improved by market participation via appropriate aggregation services, e.g. Virtual Power Plants (VPP). A comprehensive analysis of different aggregation setups has been carried out by the Danish EDISON project in the last few years [15]. The report from the EDISON project suggests three methods that can facilitate the EVs' participation in today's electricity spot market:

- 1) The retailer broadcasts the electricity price once a day to the individual EV owners and the EV owners therefore make appropriate charging schedules according to the known price and the local intelligence;
- 2) The charging strategy can be a simple time of day charging based on EV owners' empirical knowledge on when the electricity price is relatively cheap, such as at night;
- 3) THE charging of EVs can be scheduled or controlled by a fleet operator based on a contractual setup, where the central intelligence is more relied upon.

In this study, the first integration method is utilized and modified to accommodate four different charging schemes:

- 1) Night charging: the charging period is constrained to be from 7pm to 7am, and discharging is not allowed;
- 2) Night charging with V2G: the charging or discharging actions can be performed between 7pm to 7am;
- 3) 24 hour charging: the charging can be performed anytime when the EV is not in use, and discharging is not allowed;
- 4) 24 hour charging with V2G: the charging or discharging actions can be performed anytime in a day.

Since the market segment of today's EVs is primarily urban area due to the battery capacity limitation and public health concerns, this study firstly assumes that the charging infrastructure is available everywhere in the studied urban area, indicating that the EVs can be charged or discharged as long as they are not used for driving. Further, the terminology "V2G" used in this study refers to selling the battery energy back to the grid on an hourly basis at prices set the previous day; while in other literature V2G is normally referred to a mechanism that activates the provision of ancillary services.

To enable the comparison study, a mixed integer programming formulation is developed and solved using Matlab to find the optimal solution for each charging scheme applied to an individual EV. The common objective of each charging scheme, as in (1), is to minimize the cost of charging given the broadcasted electricity price $Q(i)$ and energy required for driving $E_d(i)$; meanwhile, the four charging schemes are enabled separately by turning on/off the binary variables $u_1(i)$ and $u_2(i)$.

$$\min \sum_{i=1}^N \left\{ \Delta E_c(i) \cdot Q(i) \cdot \frac{u_1(i)}{\eta_c} + \Delta E_d(i) \cdot Q(i) \cdot u_2(i) \cdot \eta_d \right\} \quad (1)$$

s. t.

$$\begin{cases} E(i) = E_0 + \sum_{k=1}^{i-1} \{ \Delta E_c(k) \cdot u_1(k) + \Delta E_d(k) \cdot u_2(k) - E_d(k) \cdot u_3(k) \} \\ \delta_{min} \cdot E_{nom} \leq E(i) \leq \delta_{max} \cdot E_{nom} \\ E_d(i+1) \cdot u_3(i+1) \leq E(i) \\ 0 \leq \Delta E_c(i) \leq P_{c,max} \cdot \eta_c \cdot \Delta t \\ -\frac{P_{d,max}}{\eta_d} \cdot \Delta t \leq \Delta E_d(i) \leq 0 \\ u_1(i) + u_2(i) + u_3(i) = 1 \end{cases} \quad (2)$$

where the planning duration is divided into N time intervals with i denotes the number of sequence and Δt denotes the time length of each interval. Decision variables $\Delta E_c(i)$ and $\Delta E_d(i)$ represent the energy charged into and discharged from the battery in each time interval respectively, while the other three binary variables $u_1(i)$, $u_2(i)$, and $u_3(i)$ indicate the on/off status of charging, V2G and driving for each corresponding time interval. To facilitate the expression, an intermediate variable $E(i)$ is introduced to represent the energy level of the battery in the end of each time interval.

Parameters E_{nom} and E_0 represent the nominal energy capacity and the initial energy of the battery in the planning period, while the charging and discharging efficiency are represented by η_c and η_d . The maximum power exchanged between the EV inverter and the electrical grid is expressed by $P_{c,max}$ and $P_{d,max}$ respectively during charging and discharging processes, which constrains the maximum energy exchanged between the EV and the grid. For battery life concerns, δ_{min} and δ_{max} are further introduced to represent the manufacturer recommended state of charge (SOC) range.

Explanations for the inequality constraints can be found in [3] wherein a similar problem is described using linear optimization by the same group of authors. Compared to the previous study, a major improvement is made in this study by formulating various charging schemes in a more generic and flexible way. Power performance of the battery is not included in this paper; however, given the energy performance within a certain time, the power performance can be derived simply by elaborating on the charging schemes e.g., constant power and constant current.

III. NUMERICAL MODEL DEVELOPMENT

For this numerical case study, the optimal charging plans for different charging schemes are derived for the next day with 5 minute resolution given the broadcasted electricity price and EV owners pre-defined driving requirement. The assumption of flawless forecasting made in this paper aims to resemble the best case scenario for different charging schemes. In practice, EV owners may not be able to precisely forecast their driving needs for the next day with 5 minute resolution in practice, which could result in higher cost for charging.

The daily optimization is further repeated over the course of a month to retrieve a more general charging performance. In this section, the selected battery model parameters, the driving information and the source of electricity hourly prices are briefly explained.

A. Battery Model

Due to its high density on power and energy, the Lithium-ion battery technology has been commonly adopted by the automotive industry for vehicle electrification. In this study, a 28kWh Lithium-ion battery is emulated to represent the battery of a medium size family car in Denmark. The SOC range is set to between 10% and 90%, and the efficiency of charging and discharging are both assumed as 90%. When the EV is grid connected, the maximum power of charging and discharging $P_{c,max}$ and $P_{d,max}$ are both set to 4kW, meaning the maximum power drawn from grid is 4.4kW during charging and the maximum power received by grid is 3.6kW during discharging. When the EV is used for driving, the maximum power discharged to drive the motor is not constrained by $P_{d,max}$ as the discharging power is dependent on the driving needs e.g., acceleration, and can therefore be much larger than 4kW. For every single day, the initial SOC at 00:00 is assumed to be 50% to guarantee the need for very early morning driving. This assumption also indicates the energy exchanged between the battery and the grid (disregarding the round trip efficiency) within a day is equal to the energy used for driving in that day.

For the emulated Lithium-ion battery, a general relationship between the lifecycle and the Depth of Discharge (DOD) is illustrated in Fig. 1.

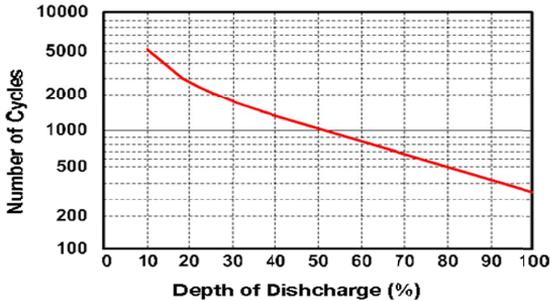


Fig. 1. Lifecycle vs. DOD of a Lithium-ion battery [17]

This relationship is approximately expressed by an exponential equation, as in (3), to support the later study on battery lifetime estimation.

$$y = 4515.2 \cdot e^{-0.0283x} \quad (3)$$

where x is DOD in %, y is the number of expected cycles corresponding to any given value of x .

B. Driving Information

As few electric vehicles are already on the road, to support the related studies of EVs, a general assumption is taken in the way that vehicle electrification would have little impact on vehicle owners' driving pattern. In this study, driving information is taken from the 2003 AKTA survey[16], in which 360 cars in Copenhagen were tracked using GPS from 14 to 100 days. Due to the data incompleteness, the full-month

record of the vehicle no. 32139 for March 2003 is picked out to support this study. The original data format is illustrated in Table I. Following the EV mileage assumption of 11kWh/100km, the AKTA data is converted to energy required for driving with 5 minute resolution as shown in Fig.2. The frequent driving behaviors within a day are due to the fact that the selected vehicle is owned by a medium size family and shared by its family members.

TABLE I
SAMPLE OF DRIVING DATA FROM 2003 AKTA

Start	Finish	Duration	Distance(m)
2003-3-2 9:31:57	9:40:23	0:08:26	21278
2003-3-2 9:44:21	9:46:59	0:02:38	1685
2003-3-2 10:45:38	10:50:53	0:05:15	2855
2003-3-2 10:55:56	11:00:14	0:04:18	2336
2003-3-2 12:58:36	13:02:24	0:03:48	2206
2003-3-2 15:24:21	15:27:34	0:03:13	2110
2003-3-2 17:23:21	17:26:09	0:02:48	1658
2003-3-2 18:41:00	18:44:57	0:03:57	2587
2003-3-2 18:48:39	18:52:54	0:04:15	2689

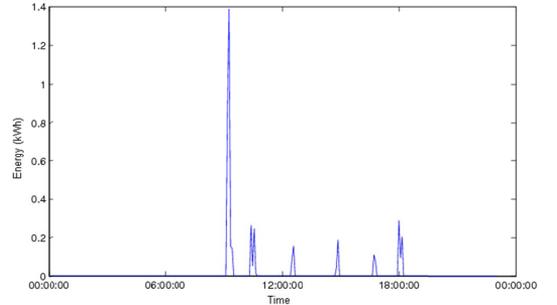


Fig. 2. Energy required for driving with 5 minute resolution on March 2nd

C. Electricity Price

The information of hourly electricity spot price of the Nordic power market is published and recorded on a daily basis by the market operator Nord Pool Spot. To guarantee the time consistency between electricity price and driving information, the electricity price of DK-west in March 2003, as illustrated by the figure on the left in Fig.3, is used for this study. The figure on the right in Fig.3 depicts the hourly electricity price on March 2nd, which is used in the later case study.

With its average wind power production covering more than 25% of its annual electricity demand, the region DK-west is known as a good representation of a future energy system with large-scale stochastic renewable resources. In such a context, the volatility of the electricity price in DK-west is also relatively high, which to a great extent benefits the V2G operation. For other regions with much less price volatility such as DK-east, the V2G operation could hardly incur extra benefits due to the round-trip energy loss unless it is traded as ancillary services which is not considered in this study.

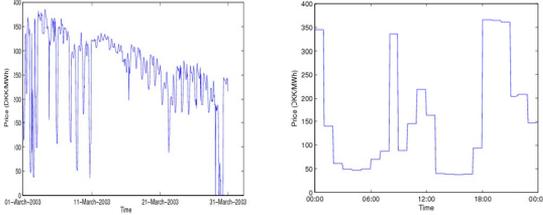


Fig. 3. Hourly electricity price of DK-west in the month of March 2003 (to the left), and on the day March 2nd (to the right)

IV. RESULTS AND DISCUSSIONS

In this section, the intra-day and the monthly charging behavior of the four different charging schemes are illustrated, and the short term economic performance, the lifetime consumption as well as the annualized cost for each charging scheme are calculated and compared.

A. Intra-day Performance

The result of an intra-day study for March 2nd, is illustrated by Fig. 4, where the blue line represents the energy requirement for driving and the red lines represents the energy charged (positive)/discharged (negative) for different charging schemes. Among the charging profiles, it can easily be found that the hours with cheap electricity are mostly selected for all schemes; however as the lowest electricity price occurs around 3pm, for the 24 hour charging scheme, the charging is performed in that period instead of midnight. For charging schemes with V2G, charging and discharging in non-driving periods become much more frequent in order to profit from electricity arbitrage.

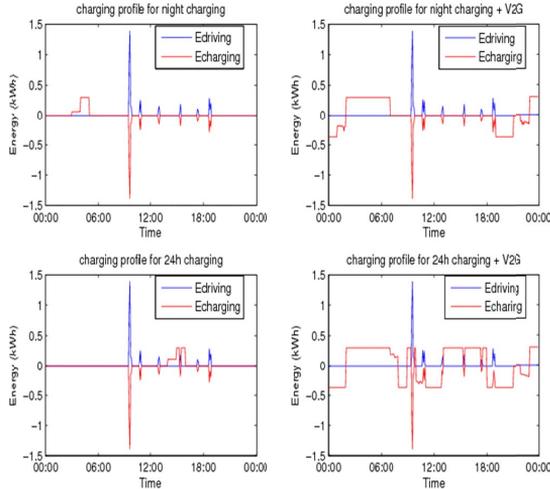


Fig. 4. Charging profiles with 5 minute resolution on March 2nd 2003

The corresponding SOC variations for different charging schemes are given in Fig. 5.

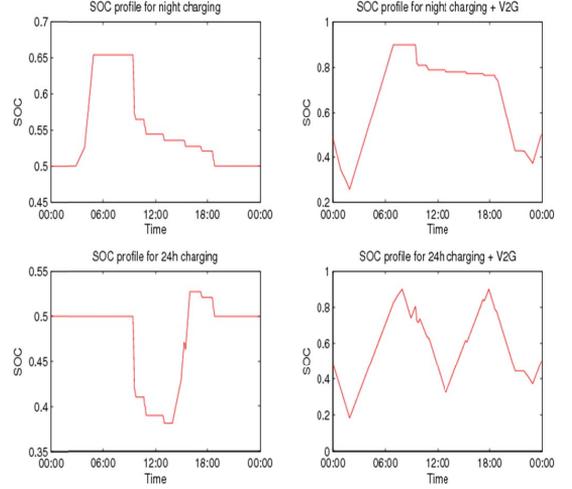


Fig. 5. SOC profiles with 5 minute resolution on March 2nd 2003

The resulting charging costs for different charging schemes on March 2nd 2003 are listed in Table II. For the intra-day case, the charging schemes with V2G options are obviously much more cost-effective than the other two due to the enriched flexibility; while the difference between the night charging and 24h charging is very small as the cheapest electricity price in the day time is very close to the cheapest electricity price at night.

TABLE II
CHARGING COST COMPARISON FOR MARCH 2ND 2003

Charging Options	Charging Cost (DKK)
night charging	0.227
night charging + V2G	-3.1785
24h charging	0.1816
24h charging + V2G	-6.3705

B. Monthly Performance

By repeating the intra-day simulation, the charging profiles and the charging costs can be derived rather simply. As presented in Table III, the charging option “24h charging + V2G” is the least expensive, which costs approximately one third of the most expensive option “night charging”. Again, there is little cost difference between “night charging” and “24h charging” due to the fact that cheap electricity periods are mostly in midnight.

TABLE III
CHARGING COST COMPARISON FOR MARCH 2003

Charging Options	Charging Cost (DKK)
night charging	33.4762
night charging + V2G	16.1366
24h charging	33.3772
24h charging + V2G	10.7202

Among the various ways of assessing the lifetime consumption of a battery, the rainflow counting algorithm simply counts the number of cycles for each level of DOD in the operational period and assumes that the amplitude of DOD determines the fraction of the lifetime that is consumed [18]. In Figure 6, an example that illustrates how the algorithm of rainflow counting is applied is presented. The original signals, which have been randomly created, represent the observed change of SOC over a certain time period. During the counting process, if one could imagine that the original curve is rotated 90° clockwise, the shape of the curve would be similar to a pagoda roof. If a raindrop is further assumed to start falling from each peak and valley of the roof, the half cycle path belonging to a specific raindrop could be obtained as indicated by the colored lines in the middle figure in Figure 6. For instance, the raindrop that follows the blue path has a length of 90%, implying a half cycle of 90% DOD; while the green path indicates a half cycle of 60% DOD. In the histogram, the number of partial cycles with different values of DOD is counted into bins of equal width, with the bin width of 1% DOD being the granularity level considered in the counting process.

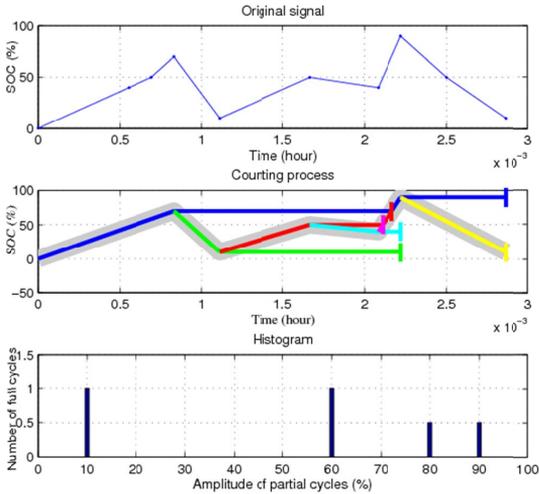


Figure 6: Illustration of the rainflow counting algorithm

By applying this post processing algorithm to the monthly charging profiles, while taking into account (3), the battery lifetime consumption for different charging schemes are calculated and illustrated in Fig. 7 and Table IV.

TABLE IV
LIFE TIME ESTIMATION FOR EV BATTERY

Charging Options	Life Usage (%)	Expected Life (year)
night charging	0.5526	15.08
night charging + V2G	0.6899	12.8
24h charging	0.5886	14.16
24h charging + V2G	0.9540	8.74

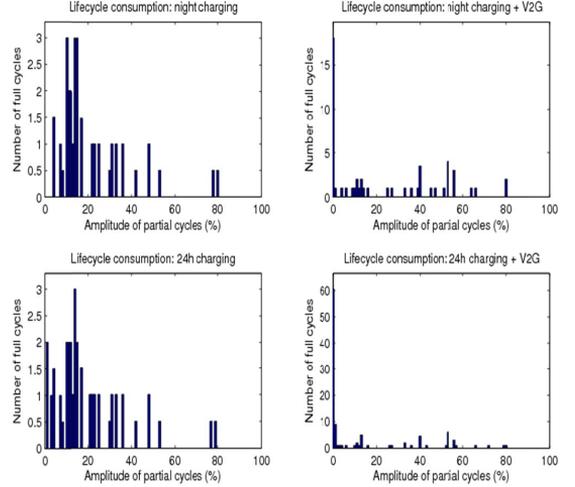


Fig. 7. Lifecycle consumption for the emulated EV battery in March 2003

As expected, the numbers of consumed partial cycles with small amplitudes are dramatically increased when the V2G options are included as illustrated in Fig.6. Although the charging option “24 charging + V2G” is found to be the cheapest among the four schemes, the associated life usage for this scheme turns out to be the largest. 0.95% of the total battery lifetime has been consumed for the charging scheme “24 charging + V2G” in the studied period March 2003, and the expected battery life is therefore reduced by almost half compared to the night charging scheme.

C. Annual Cost Comparison

To provide an informative overall comparison, a simple approach is introduced by (4) to roughly estimate the annual cost C_{ann} for different charging schemes.

$$C_{ann} = (C_{cap} + C_{cha})/L_{exp} \quad (4)$$

where C_{cap} and C_{cha} represents the capital cost of the battery and the charging cost incurred during the battery lifetime respectively, and L_{exp} indicates the expected lifetime for different charging schemes. If the monthly charging cost for each scheme is assumed to be the same as the values presented in Table III, by further setting C_{cap} to 120,000DKK which roughly represents the present market price of a 28kWh Lithium-ion battery, the annual cost for driving EV can be derived for each charging scheme. The result is summarized in Table V. Among the four options, the “night charging” scheme is found as the most cost-effective solution whereas the “24h charging + V2G” is found to be the most expensive solution due to its severe impact on battery service time and the high battery capital cost.

TABLE V
ANNUAL COST COMPARISON FOR DIFFERENT CHARGING SCHEMES

Charging Options	C_{ann} (DKK/year)
night charging	8359
night charging + V2G	9569
24h charging	8875
24h charging + V2G	13859

V. CONCLUSION

This paper has provided a numerical comparison of four different optimal charging schemes, namely night charging, night charging with V2G, 24 hour charging and 24 hour charging with V2G, on the basis of real driving data and electricity price of Denmark in March 2003. Based on a best case scenario i.e. flawless forecasting, optimal charging schemes with 5 minute resolution are found by solving a mixed integer programming problem, and compared from both short-term and long-term perspective.

It has been found that the “night charging” scheme exhibits the lowest annual cost of using the EV. On the contrary, although the V2G option can to a great extent reduce the charging cost, its severe impact on the battery lifetime noticeably increases the annual cost of using the EV. This also implies the importance of judicious designs for V2G operations, which shall not only account for the value of V2G but also suppress its negative effects. Difference between “night charging” and “24h charging” appears to be small as the electricity price is normally cheap around midnight. This may indicate the need for establishing a residential charging infrastructure could come before the need for having a public charging infrastructure.

The EV economics are heavily dependent on the pattern of electricity prices and EV users as well as the other important factors, such as tax and subsidies. The study performed in this paper is therefore more informative than conclusive. To deliver an unbiased assessment of different charging schemes, collecting the sufficient representative information, refining the modeling assumptions, investigating the grid impacts and designing appropriate validation approaches are considered as future work. For the V2G possibilities, instead of providing bulk energy back to the grid as presented in this study, it would also be interesting to examine the economy of providing ancillary services to the power system operators with various risk-averse algorithms.

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A.5 Coordination strategies for distribution grid congestion management in a multi-actor, multi-objective setting

This paper was presented at IEEE Innovative Smart Grid Technologies (ISGT) conference, Berlin, Oct 2012.

Coordination Strategies for Distribution Grid Congestion Management in a Multi-Actor, Multi-Objective Setting

Peter Bach Andersen, Junjie Hu, Kai Heussen

Abstract—It is well understood that the electric vehicle as a distributed energy resource can provide valuable services to the power system. Such services, however, would have to co-exist with hard constraints imposed by EV user demands and distribution grid operation constraints. This paper aims to address the interactions between the stakeholders involved, mainly considering the distribution grid congestion problem, and conceptualize several approaches by which their diverse, potentially conflicting, objectives can be coordinated. A key aspect to be considered is the relationship between the operational planning and the handling of real-time events for reliable grid operation. This paper presents an analysis of key stakeholders in terms of their objectives and key operations. Three potential strategies for congestion management are presented and evaluated based on their complexity of implementation, the value and benefits they can offer as well as possible drawbacks and risks.

Index Terms—Electric vehicle integration, Distribution grid, Congestion management, Smart charging

I. INTRODUCTION

Grid integration of electric vehicles, distributed generation, and other distributed resources has been a driver for a range of smart grid research activities. Here, the field of intelligent electric vehicle (EV) integration is aimed at minimizing the adverse effects of introducing electric vehicles into the power system and maximizing the value for EV owners, the power system, and society as a whole.

A large part of intelligent EV integration research has been aimed at such topics as optimal charging of electric vehicles in term of charging cost [1]–[3], enabling renewable energy [4]–[6] as well as providing ancillary service to the power system [1], [7]–[9]. Such studies have primarily been aimed at system-wide power services and energy markets while not considering the distribution network. Concurrently, studies have been carried out that look at charging management solely for the purpose of avoiding distribution level grid congestion [10]–[14].

Lately, research done in [15], [16] have been striving to coordinate these objectives, i.e., to optimize the utilization of electric vehicles while still respecting the hard constraints imposed by consumers’ needs and distribution operation constraints. In [15], a conceptual framework consisting of both the technical grid operation and a market environment was proposed to integrate EVs, the activities of all the actors

including fleet operator (FO), distribution system operator (DSO) and consumers are described and the simulation results indicate that smart charging can maximize the EV penetration without exceeding grid constraints. However, further research on the coordination between FO and DSO and the interaction between FOs and consumers are not addressed clearly. A further development can be seen in [16], in which a complex scheduling problem involving consumer, fleet operator and DSO were analyzed. The results shows that both power and voltage constraints due to electric vehicle charging can be avoided while the FO and consumer can achieve the objective of minimizing charging costs and fulfilling the driving requirements. This approach requires a somewhat complex coordination between DSO and FO but can potentially deliver a very good solution in terms of optimal grid utilization and safety.

This paper aims to add to the existing research by addressing the interactions between the various actors and conceptualize several approaches, by which their diverse, potentially conflicting, objectives can be coordinated with respect to the operational constraints of the low voltage distribution grid. A key aspect to be considered is the relationship between the operational planning done by the actors and the handling of real time events which is vital for the DSO and the distribution grid that it represents.

While this paper focuses specifically on the case of EV integration, the coordination strategies presented, aiming at congestion management in general, can to a large extend be translated to a more generic demand side management perspective.

The remainder of this paper is organized as follows: Section II presents three key stakeholders along with their objectives and operational tasks. In Section III a full map of the operations identified is presented and Section IV then expands the map in the examination of three different coordination strategies. Finally, key contributions are summarized and discussed in Section V.

II. ACTORS: OBJECTIVES AND OPERATIONAL TASKS

An overview of the actors, the grid and the main control operations is presented in Figure 1. The figure conveys how the actors’ operations are coupled through interactions via a) a common physical infrastructure, b) control relations and c) other information exchange. The coordination of these operations needs to reflect each actor’s objectives as well

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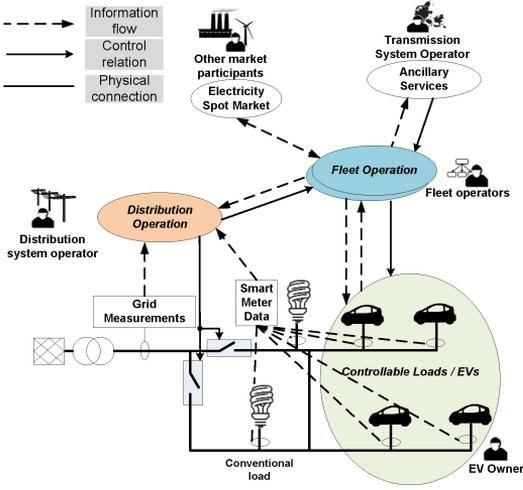


Fig. 1. Actors (stakeholders), problem domain and main information and control flows.

as operational constraints. In this problem formulation, we focus on describing the following key stakeholders and their objectives.

- Distribution System Operator (DSO),
- Fleet Operators (FO),
- Customers (controllable loads / EVs).

Other relevant influencers include the transmission system operator (TSO), other market actors and conventional demand. Their influence is conveyed via control signals, market prices, and physical network utilization, respectively. They do not have to be considered here explicitly as their role with respect to the distribution level is encapsulated via the DSO and FO.

In the following, these key actors are described in terms of objectives and the operations performed to satisfy these objectives.

A. Distribution System Operator

The main purpose of the distribution grid is to enable reliable power delivery to customers at a low-voltage level. Grid operation by the DSO is therefore aimed at effectively balancing two main objectives a) reliable grid operation and b) low cost of operation. We identify the following value drivers for a DSO:

- 1) Grid component investments,
- 2) Capacity utilization factor,
- 3) Component lifetime,
- 4) Operation cost (incl. resistive losses),
- 5) Instrumentation and automation efforts.

Provisioning of distribution grid transfer capacity is planned to be sufficient in all cases, that is, capacity is provided by the standard of annual peaks, plus safety factors for anticipated demand increases. In practice this means that distribution grids tend to have a relatively low utilization factor. On the other hand, the distribution grid planners calculate with a high

‘diversity factor’: it could be safely expected that due to the independent nature of most electricity consumption would lead to a smoothing effect that would reduce the absolute peak. As a result, secondary transformers in the distribution grids can be expected to be dimensioned at lower capacity than the total current capacity of all connected households.

The operating state of the distribution grid is limited by the following operation constraints:

- Voltage limits (voltage quality),
- Thermal limits of cables & transformers,
- MVar bands (interface to TSO), or
- Protection settings.

In this paper the focus is on the distribution grid’s ability to transfer active power.

1) *Congestion management*: The term ‘congestion’ in distribution grids refers to a situation in which the demand for active power transfer exceeds the transfer capability of the grid. As the electricity grid cannot physically get congested, the term subsumes the complex mapping of the above mentioned grid constraints to the network active power transfer capacity as seen for each connection point and the need for deferring demand (or generation¹). Whereas the constraints listed above are specified in terms of limits for specific parameters (voltage, current, reactive power, active power), they all may influence the active power transfer capability available at a connection point. Their mapping is non-trivial, as it depends on properties of the physical infrastructure, characteristics of consumption devices and built-in control behaviours required by the respective grid code.

In general, the term ‘congestion mitigation’ can then be associated with two types of strategies: a) to (locally) increase the transfer capacity by means of reactive power and voltage control and b) by coordinating the throughput via deferral or curtailment of demand [17]. Both strategies aim at increasing the utilization factor of the distribution grid.

Here, the term ‘congestion management’ explicitly refers to strategies of type b), which aim at the coordination of active power demand with respect to congested grid locations. It can be assumed that available strategies of type a) will be exhausted before type b) strategies are applied. Building on the proposal in [17], the base case for congestion mitigation will be considered active power curtailment.

2) *Distribution System Operation Today*: DSO tasks in conventional system operation, are mostly focused on ‘off-line’ tasks related to asset management and maintenance. Distribution systems today tend to be weakly monitored as compared to transmission grids, and controlled in a decentralized fashion on the basis of preconfigured local controls (e.g. by means of grid codes and protection settings). Supervisory control is then reduced time-of-day controlled adaptation of control settings, configuration management in response to outages and maintenance related challenges.

Key Operations:

- Grid dimensioning (incl. contingency planning and load curve estimation),

¹For the remainder of this paper, the perspective of distributed generation is implied.

- Maintenance and outage related topology reconfiguration,
- Adjustment of transformer taps,
- Fuses and relay operation,
- Fault-analysis and repair.

3) *Operations in active distribution grids*: To illustrate a future operation scenario with a higher level of automation, it is considered how the above operations can be extended with additional online- and data intensive operations. In order to identify and solve congestion problems, the DSO requires additional measurement equipment and/or technology enabling the anticipation of load patterns and grid 'bottlenecks'.

Key Operations for DSO congestion management in 'advanced' distribution grids:

- Demand forecasting
- Grid state estimation
- Online grid measurements
- Real-time intervention in case of unexpected deviations challenging grid reliability
- Meter data collection and aggregation

economically and reliably and shows a relation between VPPs and DSO. In this control system, several families are supplied under one feeder and they own controllable devices, i.e., electric vehicles, besides some conventional load, such as light, TV etc. For these controllable devices, they are divided into two groups according to the method controlled by the VPP, one group is directly controlled by the VPP, which means an extra cards or relays are installed on the user's device, and the VPP can turn on/off the devices; another group is controlled by price, in which the devices are assumed to be price-responsive. VPP starts to make an energy schedule for its customers with the purpose of minimizing the electricity cost and meanwhile fulfilling their requirement. This problem can be formulated as a linear programming or dynamical programming way [1], [2]. The congestion problem may first happened during the scheduling making, this problem should be solved by the coordination between DSO and VPPs. After the charging schedule was set up, ideally, the users are expected to totally follow the schedule. However, in general, deviation may happen. With the purpose of avoiding the possible congestion (happened again in real time), DSO will monitor the system's operation conditions dynamically and coordinate with VPPs. The following subsection will discuss the mechanism of solving these congestion problems.

B. Fleet Operators

The fleet operator (FO) is a commercial entity that aggregates a group of EVs in order to actively integrate them into the power market, and in so doing, utilizing their charging flexibility to meet a financial goal. The financial goal could be to achieve savings on the purchase of energy or make earnings by selling ancillary service products or, possibly, a combination of the two.

A FO follows the concept of a 'virtual Power Plant' which was first introduced to allow market participation for distributed energy resources.

In the current European power and energy markets, the FO could be a retailer with either a load balance or production

balance responsibility, depending on the market/service that the FO would address.

The value drivers for a FO are:

- 1) Maximize profits or minimize costs by participating in markets.
- 2) Providing services (cost reductions, convenience etc.) that will attract EV owners as customers.

Due to the participation in markets and customer services, the FO is subject to operating constraints defined by contractual commitments:

- Market schedule (energy/h)
- Customer demand (driving needs)
- TSO driven ancillary service requirements (e.g. reserve capacity)

How the economic value obtained through the market is shared with the customers would be business case specific to the FO. It is also assumed that the FO would maintain a Service Level Agreement (SLA) with its customers that would dictate the degree to which it may control and manipulate the EV charging patterns to achieve goals other than customer driving. This would represent a trade-off between energy savings and EV driving availability that should be understood and accepted by the customer.

The operations of the fleet operator can be divided into fleet level operations and individual level operations as follows. Fleet level:

- Selection of market products and services
- Contracting
- Market/service forecasting

Individual level:

- Customer SLA management
- Driving pattern prediction

C. Customers

The customers, here EV owners and drivers, are not assumed to be particularly interested in grid issues. Their main value drivers are expected to be:

- 1) Availability of EV for driving
- 2) Total cost of ownership/energy

It is assumed here, that the customer will opt for convenience and delegate most of the charging control to the FO. The customer is expected to rely on the frame conditions expressed in the SLA for the daily charging management for 'typical' and predictable driving patterns. An optional feature would be to let the customer communicate his or hers exact driving intentions to the FO. This would strengthen the FO ability to utilize the specific EV's flexibility. The main operations of the customer, besides transportation, would then be:

- Accept, and possibly modify, the SLA with the FO.
- Inform the FO of any non-typical driving needs.

III. MAP OF OPERATIONS

The operations outlined above will in this section be mapped graphically to enable an analysis of different coordination strategies.

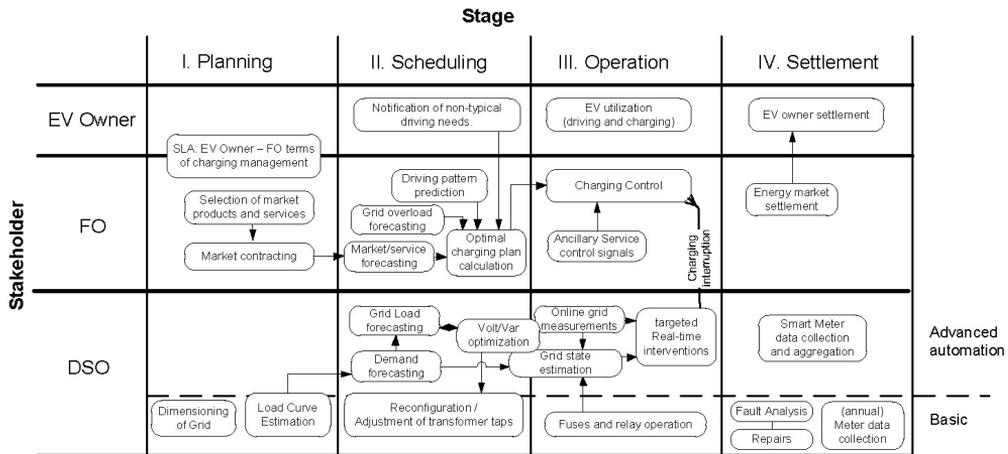


Fig. 2. Map of base-case operations.

A. Analysis Framework

In this section a classification approach is introduced, based on the understanding that the coordination approach is both an automation problem and a market design problem.

A widely accepted hierarchical decomposition of process control into four functional levels describes integrated industrial automation [18]:

- Level 4: plant(s) management
- Level 3: production scheduling and control
- Level 2: plant supervisory control
- Level 1: direct process control

This level-hierarchy is associated with several characterizing parameters, including e.g. time scale, time resolution, planning horizon, and hierarchical dependency of objectives. No single one of these parameters can be considered directly decisive for forming the levels, but together they generate the need for distinguishing qualitatively different levels of automation. The *hierarchical* dependency of objectives, i.e. that one level is *higher* and another is *lower* in ordering, is associated with the means-ends structure of objectives: A higher-level objective is broader in scope and more closely associated with the business objectives of the respective process, and thus ‘higher’ in the value chain; a lower-level objective, in contrast, is there to support and enable other process functions.

In the present multi-actor, multi-objective setting, the single hierarchy does not hold: different actors have different objectives, and yet they must interact with respect to the same process. The present means-ends perspective shall be stripped from the automation hierarchy, to allow for a high-level map of operations. Key elements to be captured in the new map are:

- Key operations and their allocation to actors
- The association of operations with a time scale including a distinction of operational and administrative functions

- The possibility to map interaction sequences between operations

Removing the means-ends perspective, we are left with a mostly time-driven decomposition. We consider the following fundamental stages:

- I. Offline Planning
- II. Online Scheduling
- III. Real-time Operation (Execution)
- IV. Offline Settlement

These stages model a logical sequence: each stage is based on a completion of the previous stage. The timing aspect is not essential here as certain types of operation can be performed faster with improved technology. The stages are characterized in the following:

Settlement is about the aftermath: recordings (measurements, sent commands, etc.) of executed operations are consolidated and (financial) responsibility is allocated. The operation stage is about pure execution in real-time. Plans are only executed, and unplanned events occur and physical as well as automatic controls respond without deliberation. The ‘online’ scheduling stage can in time be closely coupled with operation (e.g. reactive scheduling with a 5min resolution) or extend hours or days ahead of it. Scheduling is the stage in which available resources are best known and the platform for execution is to be prepared. Finally, the first stage, here called ‘planning’ has been distinguished from scheduling in the same fashion as unit commitment is distinguished from dispatch: Depending on the specific coordination strategy, we distinguish operations that can be coordinated in an ad-hoc fashion and those that provide the basis for such ad-hoc decisions. Due to these clear distinctions, the framework supports the discussion of interactions between key operation tasks for cross-stakeholder coordination for the complete process. As the operations can be associated with operation objectives of

the respective stakeholder, this map allows for an analysis of the incorporation of the respective value drivers by a given coordination strategy. This 'horizontal' level means that the operations have to be considered at the same level of abstraction. A 'vertical' perspective would unfold more details of the operations, eventually also revealing physical interactions [19]. The goal is to analyze the benefits and trade-offs involved in specific coordination strategies. Value is hereby understood in a generic sense as to contribution to a stakeholder's objectives. Given the Operation-Stakeholder allocation and the analysis of value drivers, a similar framework can be employed to also analyse value-network constellations, as exemplified in [20]. However, that type of analysis is beyond the scope of this paper.

B. Base Case Map

To establish a firm foundation for the analysis of different market-based coordination strategies, we identify a base case with a minimum set of operations that will be common to all considered congestion-coordination strategies (Figure 2). This base-case maps out the operations DSO, FO and EV owner would be required to execute in either of the coordinated congestion management schemes.

The base case uses the following assumptions:

- As discussed in [15] and [19], the introduction of controllable demand with significant power capacity such as that of electric vehicles implies a significant risk for distribution assets. To avoid potentially harmful charging configurations, we include the concept of an 'emergency brake' in all EV charging post: it enables the unconditional interruption of EV charging on request by the DSO. It could be implemented on the basis of a 'keep-alive' signal, the failure of which would immediately interrupt the EV charging process
- The maps allocate all optimization and coordination intelligence to the FO. It is understood that many of the operations could be implemented using distributed algorithms e.g. in the electric car or charging post.
- Vehicle-to-Grid (V2G) is not considered in this publication. The technology's potential for congestion relief and its impact on power quality are, however, relevant for congestion management and should be further addressed in future publications.

IV. COORDINATION STRATEGIES FOR CONGESTION MANAGEMENT

Approaches to the congestion problem are outlined and then classified and analysed using the map described in the previous section. All three strategies represent very new approaches to distribution grid congestion management and none of them have been investigated in very great detail.

The strategies investigated are:

- Distribution grid capacity market
- Advance capacity allocation
- Dynamic grid tariff

For each approach a new map is drawn where operations required specifically for the strategy in question are presented

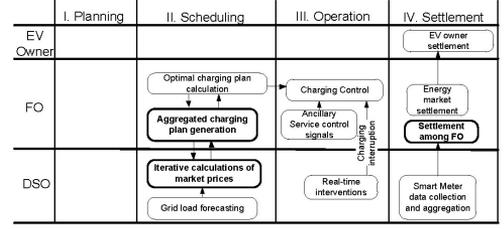


Fig. 3. Distribution Grid Capacity Market.

in bold. Shared supporting operations beyond the main trace of operations have been omitted for compactness.

To describe how technically and administratively demanding it would be for a DSO or FO to implement and operate the new procedures required by the coordination strategy the parameter *complexity* is used. A second parameter *value* denotes the degree to which the strategy would help the stakeholder achieve its operational goal. Finally, the parameter *risk* describes potential problems associated with the respective strategy in context of a currently uncertain external environment.

A. Distribution grid capacity market

As proposed in [21], this strategy would require a new market for trading distribution grid capacity. For this paper the term 'Distribution Grid Capacity Market' is used; Also a new role 'market operator' is introduced which is responsible for market operation. The FO will submit requests for their 'aggregated schedule' consisting of their scheduled consumption for each node (aggregated capacity), in response they will receive a price for each node, reflecting the respective congestion, and are requested to update their charging schedules. The process is iterated until all constraints are satisfied. The concept used in this strategy can be found in a similar form for the power transmission system [22].

1) Operation sequence:

- First, the FO will make an aggregated energy schedule for EV owners based on its objectives. Afterwards, this aggregated schedule will be sent to the market operator.
- The Market operator will generate a price for the grid capacity according to the schedules. This price is associated with the power difference between the sum of scheduled power and upper power limits of the grid.
- FOs would inform the market operator of their new energy schedule under the initial price. The schedule can be calculated based on the marginal value of a utility function, e.g., cost function in term of the power deviation or satisfaction degree with the 'preference difference' (the difference between energy schedule after congestion management and energy schedule before congestion management).
- The market operator then determines whether the distribution grid is overloaded or underutilized and comes up with a new corresponding price. After a certain number

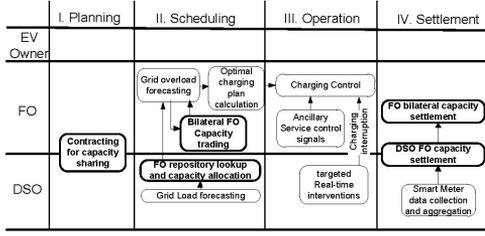


Fig. 4. Advance Capacity Allocation.

of iterations, the price will eventually converge and accepted by all FOs, which establishes a binding charging schedule.

2) Evaluation: Complexity:

With this strategy, a new market is required which means that the corresponding platform for trading grid capacity needs to be designed and implemented. Also, new communication flows are needed to support the market operations. The market itself will be rather complex to establish and operate.

A lot of complexity is transferred from DSO to the capacity market. Here the DSO will be required to provide the measured and estimated power information to the market operator. The FOs will take on the task of trading capacity and rescheduling the energy consumptions for their customers etc..

Value: With this new market, FOs will have more flexibility to trade and utilize the grid capacity of a distribution system. If the market and capacity information is reliable and well-designed it will ease the operation of the DSO, enable a comparatively high utilization factor and reliable schedules for FOs as well. A further benefit is that no actual consumption information is revealed to other market parties, as only a common congestion price is established per node.

Risk: It must be guaranteed that all FOs adhere to the rules of the market. Another risk lies in the algorithms used to arrive at prices based on utility functions i.e. the computational requirements and time needed for a solution to converge.

B. Advance Capacity Allocation

The simple concept behind this strategy is that the DSO could identify and pre-allocate available capacity by defining a conservative static capacity limit (kW) for each feeder-line based on the capacity rating of the respective transformers and cables and the expected conventional load curves. The EV-equipped households attached to a certain feeder-line would then be given a certain share of available capacity which would be allocated to the FO representing them. To avoid inefficient utilization of available grid capacity due to unused capacity shares, a second step is added to the strategy where FOs can trade their allocated capacity in an over-the-counter manner.

1) Operation sequence:

- The 'Contracting for capacity sharing' operation would involve letting the DSO know the mapping between grid

connected EV-equipped customers and FOs and then determining how capacity is shared.

- During the scheduling stage, the DSO would via grid load forecasting estimate the available capacity and communicate this to the FOs as defined in the contracts established in the planning stage. After having received its share, the FO could then optionally engage in capacity trading with other FOs operating on the same feeder.
- The DSO should be informed of the bilateral capacity trading so that, in case of violations (i.e. total load observed from EV charging in specific part of grid exceeds sum of allocated shares) penalties for violations can be appropriately placed at the responsible FO.
- Finally the strategy would involve settlement both between DSO and the individual FO and possibly an internal settlement between the FOs that engaged in the bilateral trade.

2) **Evaluation: Complexity:** Here, rather than dimensioning the physical characteristics of the grid depending on load profiles and simultaneity factors, the DSO would limit the controllable load based on the physical characteristics of the grid. In addition to the location-based grid capacity the DSO would also need to map each grid customers endpoint to an associated FO. There is also some complexity in how the FOs will trade capacity internally and how violations of grid capacity will be dealt with in the settlement stage when trading has been involved.

Value: This strategy represents a rather simple coordination mechanism between FOs and DSOs. The DSO is only required to communicate a single value (capacity) to each FO and is then removed from the equation until the settlement stage. This will simplify the responsibilities of the DSO considerably and leave the detailed capacity allocation to the entities directly in control of EV charging i.e. the FOs. There are also advantages to the FO since it will see a guaranteed capacity, free from stochasticity, early in the planning stage. Early information is valuable to an FO attempting to optimize charging to meet a variety of goals such as market services and individual driving needs.

Risk: There is the risk that a single kW limit set-point per grid node is too crude a mechanism to handle thermal loading - any unexpected change in base load during operation may void the DSO's estimation of capacity shares which has been handed out to the FOs during scheduling. The risk in this approach also lies in the effectiveness and reliability of the FO bilateral capacity trading. If the FOs can not be trusted to handle the management and trading of capacity among themselves, there will be the need of a more formal framework, e.g a market, and new definitions of responsibilities, such as the balance responsible parties seen in the energy market.

C. Dynamic Grid Tariff

In this solution, the distribution system operator generates a time and grid-location dependent price for grid usage based on expected nodal consumption levels.

The DSO anticipates the size and the price-responsiveness of the load at critical grid nodes and calculates the price to

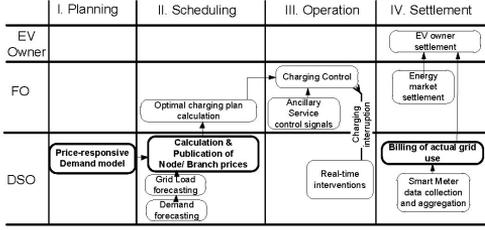


Fig. 5. Dynamic Grid Tariff.

optimally reflect the expected congestion problem. FOs will then see a dynamic nodal tariff and can make an optimal schedule with respect to the e.g. spot price and dynamic grid tariff.

The method considered here has been presented in [23].

1) *Operation sequence*: The key operation aspects for this coordination strategy are outlined in Figure 5.

- In the planning stage, a distribution system operator would create models for the price-sensitivity of relevant demand clusters. These models would be updated on a regular basis based on learning from smart meter feedback.
- In the scheduling stage the forecasted demand, grid situation and present spot market prices will be employed to calculate appropriate branch prices for distribution grid utilization.
- The dynamic tariff is published to subscribers. The adapted branch prices are received by the fleet operator and employed to compute an optimal charging plan.
- During the operation stage, the charging schedule is executed. In case of severe underestimation or fluctuations of the actual demand, DSO controlled interruptions may occur in real-time.
- For settlement the timed consumption data is collected by the responsible DSO and the published prices will then be employed to bill the actual grid usage individually.

2) *Evaluation*: **Complexity**: The main characteristic feature of this approach is the simplicity of the interactions and also the simplicity of integrating simple prices in distribution grids.

The implementation complexity is high on the side of the DSO. This scheme cannot be established safely without interruptibility of the vehicle charging.

For the Fleet Operator–Consumer interaction, the establishment of a satisfactory service quality may require a special attention to potential bottlenecks in the system from the side of the Fleet Operator.

Value: As compared to the base case, this model enables an increase of the grid utilization factor. The small number of participants at a feeder level means that random behaviour (fluctuation consumption level) might be stronger than the price sensitivity of the controllable demand. Even though the increase of the utilization factor is therefore highly uncertain, the simplicity of the approach could justify its implementation.

TABLE I
STRATEGY OVERVIEW

Actor	Complexity	Value	Risk
<i>Distribution Grid Capacity Market</i>			
FO	High	High	Low
DSO	High	High	Low
<i>Advance Capacity Allocation</i>			
FO	Medium	High	Low
DSO	Low	Medium	Medium
<i>Dynamic Grid Tariff</i>			
FO	Low	Low	High
DSO	Medium	Medium	High

For fleet operators and consumers, the benefits are also indirectly associated with the increased grid utilization. A further benefit can be seen in the flexibility this approach offers with respect to integrating other flexible demand units, as the price, in theory, could interpreted by any unit.

Risk: It is unclear whether a meaningful price-sensitivity of demand can be established.

There is a risk that there is no ‘right’ price to avoid overloading, if a sufficient number of EVs is connected to the same feeder, there is no way for them to negotiate capacity utilization in the given framework. Due to the required interruptibility, the high chance for unplanned charging interruptions also implies an additional risk is on the side of the Fleet Operator / EV Owner.

V. DISCUSSION AND CONCLUSION

This paper has investigated the concept of congestion management for distribution grids, detailing the operations and interactions of two main stakeholders in three different coordination strategies. The purpose of the analysis was to highlight the cross-actor dependencies that each such strategy entails along the operation timeline, and thus to globally assess complexity, value and risk for each strategy.

Table I summarizes these evaluation parameters across the strategies and stakeholders. In this table the customer is represented by the FO.

The ‘distribution grid capacity market’ is expected to offer high value and low risk for both FO and DSO assuming a formalized, optimal and secure framework supplied by a well-designed market. Such a market, however, may represent the most complex strategy to implement, which may hinder or delay its real-life implementation.

‘Advance grid capacity’ is relatively easy to implement, but would require over-the-counter trading to efficiently use available grid capacity. The strategy removes complexity from the DSO but some risk may have to be managed due to the bilateral FO trading and the advance capacity allocation might require more conservative estimates of the available capacity. The FO gains high value from early information on capacity availability.

‘Dynamic tariffs’ would also be easier to implement than a capacity market, but may prove challenging to the fleet operator due to added uncertainty and a possible conflict with system-wide smart charging schemes. It could also impose some extra risk for the DSO to rely on prices rather than hard capacity limits when considering individual feeder lines.

A few general observations can be summarized as:

- Grid considerations will have to co-exist with other objectives in the charging management of EVs.
- Coordination and information exchange in earlier stages can reduce complexity and benefit both the FO and DSO.
- There may be a trade-off between ease of strategy implementation and optimality. A compromise may be necessary for the first real-life implementations.
- A suitable strategy for coordination between DSOs and FOs will improve each stakeholders ability to reach its objectives considerably.

The analysis framework developed in this paper can be considered sufficiently generic for analysing operations with respect to other distributed resources.

An important mechanism included in this paper is the ‘real-time intervention’ functionality used by the DSO. This last-resort ability to directly and immediately reduce or disconnect charging may be a prerequisite for the deployment of effective coordination strategies.

In the end, it is hoped that this paper contributes to a better understanding of the multifaceted challenge of EV charging and helps the development of open, robust, and meaningful strategies for low voltage grid congestion management.

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VII. BIOGRAPHIES



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A.6 Coordinated charging of electric vehicles for congestion prevention in the distribution grid

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Coordinated Charging of Electric Vehicles for Congestion Prevention in the Distribution Grid

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Abstract—Distributed energy resources (DERs), like electric vehicles (EVs), can offer valuable services to power systems, such as enabling renewable energy to the electricity producer and providing ancillary services to the system operator. However, these new DERs may challenge the distribution grid due to insufficient capacity in peak hours. This paper aims to coordinate the valuable services and operation constraints of three actors: the EV owner, the Fleet operator (FO) and the Distribution system operator (DSO), considering the individual EV owner's driving requirement, the charging cost of EV and thermal limits of cables and transformers in the proposed market framework. Firstly, a theoretical market framework is described. Within this framework, FOs who represent their customer's (EV owners) interests will centrally guarantee the EV owners' driving requirements and procure the energy for their vehicles with lower cost. The congestion problem will be solved by a coordination between DSO and FOs through a distribution grid capacity market scheme. Then, a mathematical formulation of the market scheme is presented. Further, some case studies are shown to illustrate the effectiveness of the proposed solutions.

Index Terms—Congestion management, distribution grid, electric vehicles, optimal charging schedule.

I. INTRODUCTION

A. Aggregated Charging of EVs

OTHER THAN fulfilling its basic transport function, EVs, as smart grid assets, can provide a large number of valuable services, e.g., meeting the balancing requirements for energy suppliers with stochastic renewables, providing regulation services to the system operators, and modifying the demand curves to defer the network expansion, etc., [1]–[7]. As a result, a new business entity, namely EV fleet operator (FO) has emerged which aims to capture the business opportunities by providing the multiple services of EVs. Alternative names for an EV FO are used such as EV virtual power plant, EV aggregator or charging service provider. The new entities could be independent or integrated in an existing business function of the energy supplier; however they all share a list of commonalities as following:

- 1) Same mission:
 - Guarantee driving needs of the EV owners;

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Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

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- Coordinate and support the valuable services and operation constraints of EV and power system operator;
 - Maximize the renewable energy.
- 2) Similar methods:
 - Implement centralized control/marketing method to maximize business values [1]–[7];
 - Optimize the charging process of EVs [6], [8]–[11].

However, the function of the distribution grid may be challenged when FOs try to achieve these objectives, because the increasing size and number of consumption units, e.g., EVs can cause problems in peak hours [12]–[16]. Mainly two issues are considered in the literature when discussing the possible challenges in a distribution grid with increasing DERs, they are voltage drops and thermal overloading of transformers and cables. Focus in this study will be on the prevention of the thermal overloading of the transformers and cables, which is also known as congestion management. In the following of this section, we first give an overview on the centralized and market-based coordination strategies for grid congestion management. Then, the motivation and contribution of this study is presented.

B. Centralized Control of EVs for Grid Congestion Management

Lately, research done in [17]–[19] have been aiming to coordinate these multiple objectives centrally, i.e., to optimize the charging cost of EVs as well as respecting the hard constraints imposed by EV owner needs and distribution grid operation. In [17], [18], a complex scheduling problem involving EV owners, FO and DSO is analyzed. The results show that both the FO and the EV owners can achieve the objectives of minimizing charging costs and fulfilling driving requirements without violating the grid constraints. This approach requires a complex interaction between DSO and FO, but can potentially deliver a very good solution in terms of optimal grid utilization and safety. A conceptual framework consisting of both a technical grid operation strategy and a market environment is proposed in [19] to integrate EVs into the distribution systems, the activities of all the actors including the EV owner, the FO and the DSO are described and the results indicate that smart charging can maximize the EV penetration without exceeding grid constraints.

C. Market-Based Coordination Strategies of EVs for Grid Congestion Management

Alternatively, several ways of solving the congestion problem have been suggested from market perspective. Our previous study [20] has conceptualized several approaches to address the

distribution grid congestion according to their value and benefits which they can offer as well as possible drawbacks and risks and the complexity of implementation. A short description of the principles behind these strategies is given below:

- **Distribution grid capacity market**

In this method, FOs will submit power requests to DSO for their aggregated energy/power schedule on each node (aggregated capacity); in response they will receive a price for each node which reflects the respective congestion, and are requested to update their energy schedules. The process will terminate when all constraints are satisfied. The mechanisms behind the market could be designed in many ways, such as uniform price auction mechanism [21], shadow price based mechanism [22].

- **Dynamical grid tariff**

In this method [23], the DSO generates a time and grid-location dependent price for grid usage based on expected nodal consumption levels. The DSO anticipates the size and the price-responsiveness of the load at critical grid nodes and calculates the price to optimally reflect the expected congestion problem. The FO will then get the dynamic nodal tariff and make an optimal schedule with respect to the predicted spot price and dynamic grid tariff.

Besides, studies in [24], [25] investigate the coordination methods using a common price signal and the work [24], [25] share a lot of similarities. Mainly, both work use game theory to formulate an EV/demand energy consumption scheduling game. The actors are assumed to be cost-minimizing and coupled via a common signal, i.e., a common electricity price in [25] and total load of the distribution grid (a heavier grid loading means a higher price) [24]. The strategies are the daily schedule of their consumption.

D. Motivation and Contribution of This Paper

Currently the dispatch is set only based on the day-ahead electricity market and the end-users' need for energy services. Traditionally, demand takes place when needed and the challenges in the distribution grid created by the EV aggregation could be solved by expanding the grid to fit the size and pattern of demand. As an alternative, it is assumed that the distribution grid company can benefit more by making the consumers shift demand consumption from one given period to another, after identifying the long-term marginal costs of reinforcement of the grid. Considering the new opportunity, a new scheme using both the day-ahead electricity market and the distribution grid state to set the dispatch should be established, which can enable the power system balance and the distribution grid congestion management. In general, two schemes are qualitative analyzed and proposed [12]: 1) distribution grid congestion management first, then energy system balance or 2) vice versa. Both the merits and demerits of these two strategies are well discussed in the report [12].

The present study aims to investigate the coordination strategy among DSO, FOs and EV owners based on the basic concept in [20], [12], specifically, the conceptualized proposal of “distribution grid congestion management first, then energy system balance” in [12] and the distribution grid capacity market in [20], by making them into concrete optimization

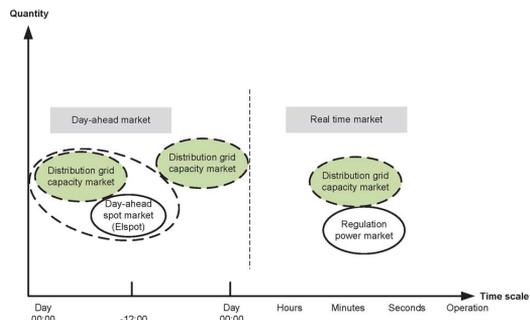


Fig. 1. The proposed distribution grid capacity market can be an integrated part of the current power markets.

problems and by showing detailed case studies. In this study, a framework is proposed which can minimize the charging cost of EVs as well as respecting to the hard constraint imposed by the EV owners and DSO. The proposed framework consists of linear programming technology based optimal charging of EVs and shadow price mechanism based distribution grid capacity market.

Fig. 1 illustrate the proposal of integrating the new proposed distribution grid capacity market into the existing power markets. It is emphasized that the market scheme is flexible and scalable, in the fig, the “distribution grid capacity market scheme” is placed in three position, which represent three different time periods, i.e., day-ahead and intra-day period for congestion prevention, real time period for congestion relief.

There are mainly two research contributions in this study. Firstly, we recommend and test a distribution grid capacity market set up enabling the distribution congestion prevention, in which multiple FOs are involved. Secondly, the proposed market framework is flexible and scalable in diverse control schemes, such as the mechanism elaborated later specifically for the day-ahead period can be also adopted for the control situation in the period of intra-day and real time, the mechanism designed for EVs can be also used for other appliances which have the capability of altering their consumption pattern with limited impact on their primary energy service, such as theoretically controlled loads.

The remainder of the paper is organized as follows: In Section II, a general explanation is given on the methodology for congestion prevention, i.e., the proposed market framework. Section III mainly presents the mathematical formulation of the congestion issues into a subgradient method based distribution grid capacity market set up. Then several case studies are illustrated in Section IV to facilitate the understanding. Finally, discussion and conclusions are made in Section V.

II. METHODOLOGY FOR CONGESTION PREVENTION: SYSTEM ARCHITECTURE, OPERATION PRINCIPLE

As discussed in [26]–[28], each distribution grid has a different history, such as in some cases congestion is first expected to emerge in the medium voltage grid, while in other grids the low voltage grid is considered to be more critical. In this study, a low voltage grid is used for illustration purpose, but the proposed framework holds for medium voltage grid as well.

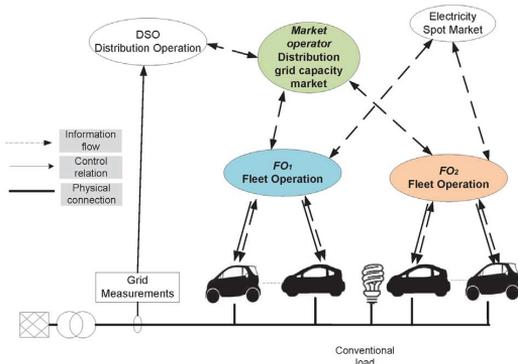


Fig. 2. A schematic of a low voltage active distribution system.

A. System Architecture, Framework Design

Fig. 2 presents a schematic of a low voltage distribution system, in which around 60–70 household consumers are connected to a 10/0.4 KV transformer (a typical Danish case), mainly connected on one feeder. In this distribution system, it is assumed that the consumers own controllable devices, i.e., EVs, besides some conventional loads, such as light or TV. These EVs are divided into two groups as illustrated in Fig. 2. One group is controlled by fleet operator-1 (FO₁), another group is controlled by fleet operator-2 (FO₂). In this hierarchical distribution system, both FOs can schedule and control their customer’s electricity consumption directly. While on the FO level, the coordination between FOs and DSO is made through the distribution grid capacity market.

Within the assumed system architecture, we propose a framework consisting of four fundamental stages [20] to operate and control this system. This framework is a fully charging profile management for integrating EVs into the distribution grid smoothly.

- 1) Energy schedule of the FOs without congestion management—Offline scheduling. Both FO₁ and FO₂ need to predict the energy requirements (driving patterns) of their customers (EV owners) and plan the corresponding expected charging schedule for the EVs. The methods of estimating the energy requirements and setting up the charging schedule may be different, but in general, the FOs try to minimize the charging cost of their customers as well as guarantee the driving requirements of the EV owners.
- 2) Market based approach for distribution grid congestion prevention—Offline scheduling. The distribution grid capacity market will take effects if congestion happens. FOs trade the power capacity of the distribution grid in this market. During the negotiation of the market, a shadow price will be issued by the market operator in the time slot where congestion happens. Then this shadow price will be sent to FOs, FOs will add up the shadow price with the predicted spot price and utilize the new price to set up a new charging schedule. Again, the new schedule will be sent to the DSO/Market operator, such iteration will be terminated until the congestion is eliminated. After congestion management, FOs bid the allowable power schedule to the

energy market, such as Nord Pool Spot market¹ in North Europe.

- 3) Online scheduling and real time control. It is valuable for FOs to utilize the online scheduling stage and make better charging schemes, the general objectives are to avoid energy imbalance and to optimally participate in the regulating power market. Usually, more accurate information is provided to the FOs in this stage, FOs can judge whether they need to reschedule the charging plan based on the utility and risk analysis. With regard to real time control, one can assume that the EVs will charge according to the plan; however, if grid normal technical operation is compromised, FO management can be overridden by the DSO operation, such as using load shedding scheme.
- 4) Settlements. In this study, the settlements are carried out with the final energy price, i.e., the sum of spot price and shadow price (Tax, transmission, distribution fees etc., are not included here).

B. Operation Principle and Assumptions

1) FO/EVs operation

- Aggregating EVs. From a practical perspective, it is assumed that EVs need to subscribe to one FO, maybe in the form of signing a contract that is valid for certain time period. Such subscription would possibly following the existing geographical areas, i.e., the neighborhood supplied by one FO, under one substation. The mobility of EV, in such context, will also require the roaming-related agreement/standards among different FOs as well as an standardized ICT infrastructure, in order to make sure the FOs can access the EV information immediately when the EVs switch FOs.
- Predicting EVs driving pattern. We assume EVs have standardized function of being able to be plug and play. In most cases, they will charge at home, which is supplied by their signed FO. By establishing a database for EV users, it is feasible for FOs to predict EVs driving pattern. Besides, EV owners are encouraged to submit their draft plan for the utilization of EVs in the next day. In few cases, they may need to charge in some other areas where belong to another FO, since the fully charged battery in morning time could sustain their daily driving requirements in most times. In such case, a roaming technology widely used in the Telecom could be an example for us, which means that FO and FO can share information.
- Optimal charging schedule generation. We assume that the charging process of EVs following a linear behavior and FOs use a linear programming technology to model the optimal charging problem of EV fleet and determine the aggregated EV charging profiles. The computation speed is quite fast for FOs.
- Interacting with DSO/Market operator. For the interactions between FOs and DSO/Market operator, it is assumed that ICT infrastructure can facilitate the communication.

¹<http://www.nordpoolspot.com/>

2) DSO/Market operator operation

- Grid state estimation. The proposed solution requires a higher level of automation on the operation of distribution grid, such as demand forecasting, grid state estimation and online grid measurements. This is not an easy task for DSO at this moment, since little real time information exists about the power flow in the low voltage grid. While in the medium voltage grid, the real time measurement is traceable in the Danish distribution systems and many other European distribution systems. The good news for the low voltage grid is the installation of the smart meters, today, in Denmark, half of all households have an updated meter that can be read remotely at least on hourly basis. With these inputs, the DSO could study the co-variation between the DERs and traditional load. Data mining technology can be used to separate the information of conventional loads from EVs would be highly necessary.
- Shadow price set up. The shadow price will be determined based on the power requirement of FOs and the capacity of transformer/line of the distribution grid. More details will be presented in next section.

III. METHOD DEVELOPMENT OF SMART CHARGING OF EVS WITH GRID CONGESTION MANAGEMENT

In this section, algorithms and models for enabling the EV charging profile management are discussed. In short, FOs predict their customers' energy requirements and make the energy schedule, which is shown in Section III-A. Then Section III-B illustrates the method for grid congestion management. A settlement example is given in Section III-C. It is noted that the main work in this study is in the stage of offline scheduling, and it is assumed that there is no schedule changes in the online scheduling period and the EVs will charge based on the schedule made in the offline scheduling stage.

A. Energy Schedule of the FOs Without Congestion Management

We provide one solution as a reference for the energy schedule setting of FOs, the solution is based on our previous study [10], in which, an optimal charging strategy has been proposed for EVs with the purpose of fulfilling EV owner's driving requirements as well as minimizing the charging cost. The solution is briefly modified and introduced as follows:

$$\text{minimize } \sum_{i=1}^{N_T} \Phi_{j,i} P_{j,i} t_{j,i}, j = 1, \dots, N_k^E$$

subject to

$$\begin{cases} \text{SOC}_{0,j} + \sum_{i=1}^{N_T} P_{j,i} t_{j,i} \geq \text{SOC}_{\text{Min},j} + \sum_{i=0}^{N_T-1} E_{\text{drive},i+1} \\ \text{SOC}_{0,j} + \sum_{i=1}^{N_T} P_{j,i} t_{j,i} \leq w * E_{\text{cap},j} + \sum_{i=2}^{N_T+1} E_{\text{drive},i-1} \\ 0 \leq P_{j,i} t_{j,i} \leq E_{\text{max},j}, i = 1, \dots, N_T \end{cases} \quad (1)$$

With the above optimization problem, the FO can generate a unique energy schedule for EV owner; the sum of the individual EV energy schedule will be denoted as $P_{k,i}^E$, and

$$P_{k,i}^E = \sum_{j=1}^{N_k^E} P_{j,i}, k = 1, \dots, N_B, i = 1, \dots, N_T,$$

where

N_k^E	Number of EVs under FO k .
N_T	Number of time slot in the scheduling period.
N_B	Number of FOs.
j	Index for the number of EVs under each FO, $j = 1, 2, \dots, N_k^E$.
i	Index of time slot in the scheduling period, $i = 1, 2, \dots, N_T$.
k	Index for the number of FOs, $k = 1, \dots, N_B$.
$\Phi_{j,i}$	Predicted day-ahead electricity market price vector.
$P_{j,i}$	Decision variable vector.
t	Length of each time slot.
$P_{k,i}^E$	Power requirements of EVs of each FO in each time slot.
$\text{SOC}_{0,j}$	Initial SOC of individual EV.
$\text{SOC}_{\text{Min},j}$	Recommended minimum SOC of the EV.
E_{drive}	The predicted individual EV owners driving requirement.
$E_{\text{max},j}$	Charge rate in term of energy of individual EV.
$w * E_{\text{cap},j}$	Recommended maximum SOC of the EV, where w is the parameter which express the charging behavior of the battery of the EV is a linear process, $E_{\text{cap},j}$ is the capacity of the battery of the EV.

In (1), the first constraint means that the available energy in the battery should be greater than or equal to the energy requirement for the next trip. The second constraint indicates that the available energy in the battery should be less than or equal to the power capacity of the battery. The third constraint represents that the charging rate is less than or equal to its maximum power rate of a charger. The physical meaning of the decision variable vector $P_{j,i}$ is to make a decision to distribute/charge the power on the certain time slots, where the charging cost can be minimized.

B. Market Based Approach for Distribution Grid Congestion Prevention

1) Analytical Analysis of Distribution Grid Capacity Market: In general, the method starts with a proposed cost function which represents the cost of the power preference difference of a FO in each time slot, e.g.,

$$\mu_k = \zeta_k(\tilde{P}_{k,i}).$$

To facilitate the understanding, we assume

$$\mu_k = C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2, \quad (2)$$

where k, i keep the same with above notation, $\tilde{P}_{k,i}$ denotes the control variable, $C_{k,i}$ means the weighting factor which are associated with the power difference, the larger $C_{k,i}$ implies a smaller difference.

The objective is to minimize the cost functions as well as respect to the constraint from DSO:

$$\text{minimize} \quad \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2$$

subject to

$$\sum_{k=1}^{N_B} \tilde{P}_{k,i} \leq P_{\text{Cap}}(i), i = 1, \dots, N_T, \quad (3)$$

where $P_{\text{Cap}}(i)$ is the power capacity specifically for all the FOs, for example, it can be estimated by the DSO after deducting the conventional loads.

This problem is a convex optimization problem and relevant research [29], [30] show that by introducing Lagrange multipliers or shadow price $\Lambda(i) \in R^{N_T}$, problem (3) can be transferred into following partial Lagrangian problem:

$$L = \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2 + \sum_{i=1}^{N_T} \Lambda(i) \left(\sum_{k=1}^{N_B} \tilde{P}_{k,i} - P_{\text{Cap}}(i) \right) \quad (4)$$

The centralized optimization problem (3) is transferred into a decentralized one with associated shadow price $\Lambda(i)$ in each time slot, with the purpose of emulating the market behavior.

Following work aims to find the optimal power for each FO and the associated shadow price on the distribution grid line. We will assume, for simplicity, the Lagrangian function has a unique minimizer over $P_{k,i}$, which denoted as $P_{k,i}^*(\Lambda)$.

The dual problem (4) is then given by

$$\text{maximize} \quad g(\Lambda) = \inf \left(\sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} \left(P_{k,i}^*(\Lambda) - P_{k,i}^E \right)^2 + \sum_{i=1}^{N_T} \Lambda(i) \left(\sum_{k=1}^{N_B} P_{k,i}^*(\Lambda) - P_{\text{Cap}}(i) \right) \right). \quad (5)$$

This dual problem (5) will be solved by projected subgradient method [31]–[33],

$$\Lambda(i)^{\omega+1} = \Lambda(i)^\omega + \alpha_\omega \cdot S(i), i = 1, 2, \dots, N_T, \quad (6)$$

where $\partial(-g)(\Lambda(i))$ is the subdifferential of $(-g)$ at $\Lambda(i)$ and $S(i) \in \partial(-g)(\Lambda(i))$, one can find $S(i) = \sum_{k=1}^{N_B} P_{k,i}^*(\Lambda^*) - P_{\text{Cap}}(i)$ with $P_{k,i}^*(\Lambda^*)$ being the solution to the following optimization problem:

$$\text{minimize} \quad \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2 + \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} \Lambda(i) \cdot \tilde{P}_{k,i} \quad (7)$$

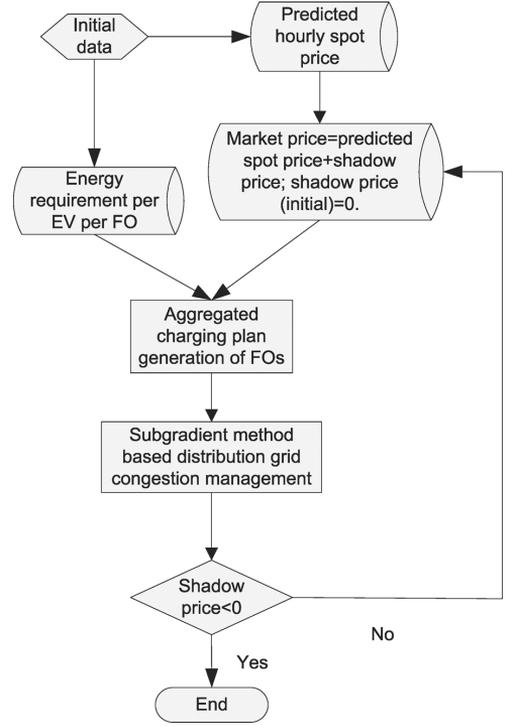


Fig. 3. Flow chart of the proposed cost and schedule adjustment algorithm.

This optimization is completely separable between various FOs, and can therefore be solved distributively. For each FO, such as FO_k , the optimization problem becomes

$$\text{minimize} \quad \sum_{i=1}^{N_T} C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2 + \sum_{i=1}^{N_T} \Lambda(i) \cdot \tilde{P}_{k,i}, \quad k = 1, \dots, N_B \quad (8)$$

Solving problem (8) for the FOs gives power $P_{k,i}^*(\Lambda^*)$ that can be used to find the subgradient:

$$S(i) = \sum_{k=1}^{N_B} P_{k,i}^*(\Lambda^*) - P_{\text{Cap}}(i) \quad (9)$$

2) *Cost and Schedule Adjustment Algorithm:* The following steps illustrate the cost adjustment algorithm which are illustrated in Fig. 3 and can mimic the trading and negotiation process in the distribution grid capacity market, when congestion happens. The algorithms integrate the mechanisms discussed in the above of this section.

- 1) FOs submit their energy schedule to the distribution grid capacity market before submitting them to the electricity spot market.
- 2) The DSO/Market operator predicts whether congestion will happens based on the schedules of FOs, if happens, go to the distribution grid capacity market, otherwise, the energy schedule is approved.
- 3) Distribution grid capacity market operation

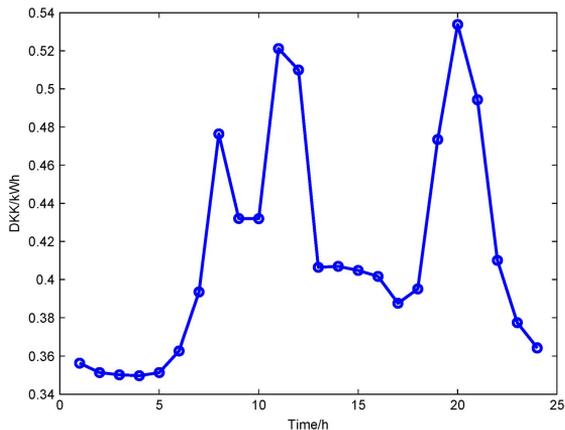


Fig. 4. Spot price in one day (12, Jan, 2011), DK-West, from NordPool, which is used as the predicted price for fleet operator.

Initialize dual variable $\Lambda(i)^\omega := \Lambda_0(i) \geq 0$, e.g., using $\Lambda_0(i) = 0$ or $\Lambda_0(i) = \Lambda(i-1)$.

loop

- With the parameter of $\Lambda(i)$, market operator determines the capacity margins $S(i)$ using (9) based on the solutions $P_{k,i}^*(\Lambda^*)$ of (8).
 - Update the variables $\Lambda(i)^{\omega+1} = \Lambda(i)^\omega + \alpha_\omega \cdot S(i)$, until the prices converge.
- 4) The new shadow price will be sent to FOs, FOs will add up this price on top of predicted spot price, recalculate the optimization problem (1), and get a new energy/power schedule $P_{k,i}^E$ and send to the DSO/Market Operator.
 - 5) Do the above calculation (step 2 and 3) again, until $\Lambda(i) < 0$, then terminate the iteration.
 - 6) Bid final energy/power schedule $P_{k,i}^E$ to the electricity spot market.

In above algorithm [31], $\alpha_\omega \in R$ denotes the step size and can be chosen as $\alpha_\omega = \alpha$ which is a positive constant, independent of k ; with such choice, the convergence is guaranteed.

C. Settlements

In the settlement stage, the sum of the electricity spot price and shadow price will be used as an energy price, and the corresponding cost for FOs are given by

$$Cost(k) = \sum_{i=1}^{N_T} (\Phi(i) + \Lambda(i)) \cdot P_{k,i}^{final}, k = 1, \dots, N_B. \quad (10)$$

IV. CASE STUDY

In this case study, a representative distribution grid is illustrated in Fig. 2. It is assumed that 60 households are connected on the feeder. Sixty percent of the consumers are assumed to have EVs which are operated by FO₁ and FO₂. Specifically, P_{Cap} represents the capacity of the transformer/cable and this capacity will be shared by FO₁ and FO₂ during the scheduling and operation period.

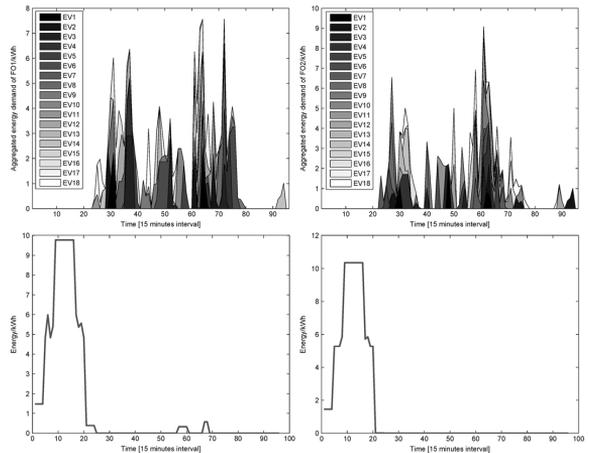


Fig. 5. Top: Aggregated energy demand of FO₁ and FO₂; Bottom: Aggregated energy schedule of FO₁ and FO₂.

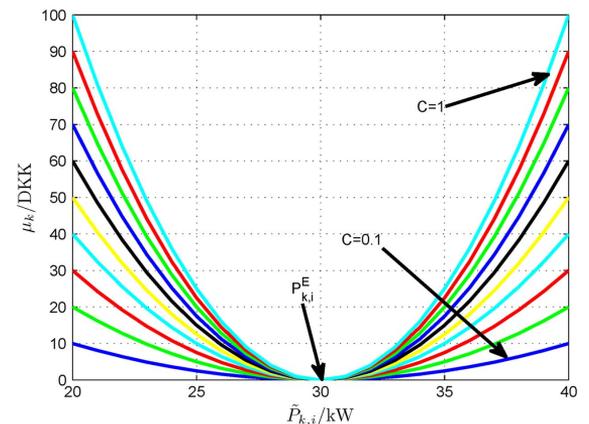


Fig. 6. A hypothetical cost function of (2), C has a stepwise increase of 0.1 from 0.1 to 1.

A. Energy Schedule of the Fos Without Congestion Management

For the EV charging schedule, the information of hourly electricity spot price of the Nordic power market is assumed to be perfectly known by the FOs, and the price data is identical with previous study [10], which is illustrated in Fig. 4. The artificial driving data of the EV fleet have been generated based on the 2003 AKTA Survey [34], in which 360 cars in Copenhagen were tracked using GPS from 14 to 100 days. Each data file includes starting and finishing time, and the corresponding duration and distance. The original data is transferred into 15 minutes interval driving energy requirements based on the assumption of 11 kWh/100 km. The energy requirements of FO₁ and FO₂ are the sum of the 18 EVs, which is illustrated in the top of Fig. 5. It may not be easy to identify the individual EV's driving energy requirements, but a general trend can be concluded that most of the driving time is located in the morning and evening periods. In FO₁, EV12 has the largest energy requirement which is 15.45 kWh. In FO₂, it is EV4 that needs the most energy

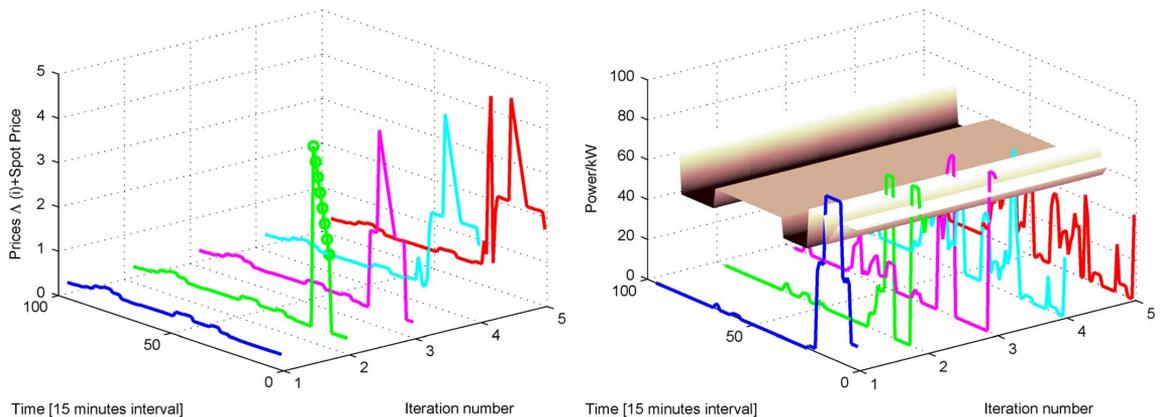


Fig. 7. **Left:** The sum of the spot price and shadow price in each iteration step. **Right:** The comparisons of FO's power schedule in each step with the power capacity.

which is 11.55 kWh. We assume that the data used for the simulation which represent the EV owners' driving requirements are perfectly known to the FOs. The 15 minutes interval is changeable rather than absolute. For other parameters:

- Battery capacity is set to 20 kWh
- SOC_o is set to 0.2 of the battery capacity
- SOC_{min} is set to 0.2 of the battery capacity
- SOC_{max} is set to 0.85 of the battery capacity
- Maximum charging power is limited to 2.3 kW, this fits with the Danish case (10 A, 230 V connection).

With this information, one obtains the aggregated charging energy of each FO, which is shown at the bottom of Fig. 5. It is observed that the charging period is concentrated on the early morning time due to the lower electricity price in that time period. We assume that the power is constant in one time slot, which means the corresponding power in each time slot can be obtained ($Energy/\Delta t$).

B. Market Based Approach for Distribution Grid Congestion Prevention

In this step, we will illustrate the effectiveness of utilizing the shadow price, i.e., $\Lambda(i)$ to facilitate the congestion management in the proposed method. It is noted that the cost function in this study presented by the quadratic function is assumed to represent the cost for the energy preference loss. The accuracy of the cost function is out of the scope of this study, the focus is to show how the FOs establish the schedule based on the cost function and the shadow price. Fig. 6 illustrates the cost function of (2) with various $C_{k,i}$, in which $P_{k,i}^E$ is set to 30 kW.

The power capacity $P_{cap}(i)$ is set up according to the trend in the real case; generally, the capacity is higher in the later evening and early morning time and lower in the day and evening time. The curve of the power capacity is shown by the surface in the right figure of Fig. 7. The weighting factor rate $C_{1,i}, C_{2,i}$ is set to 0.5 and 0.1. The value of α_ω is chosen as 0.1 in this case. Note that the variable $C_{k,i}$ and α_ω are connected, an appropriate value of the two variables can ensure smooth operation of the proposed method, i.e., the trade-off of the speed of the convergence and the accuracy of the solution. However, there is not a strict rule for choosing the parameter values. Together with the

energy schedule of FO₁ and FO₂ before congestion management, the values of power capacity and weighting factor rate, the simulations are presented in the Fig. 7. From these two figures, it can be seen that the congestion problems are solved after 5 steps. Note that in the beginning, the shadow price is zero, so the blue curve represents the same price information as the one in Fig. 4. The purpose for put this price again is to get a complete view on the change of the price. Same explanation holds for the blue power curve in the right figure.

Fig. 7 presents the dynamic process of the distribution grid congestion management. It is noted that in each iteration step, the negotiation process of the FOs in the distribution grid capacity market is not shown, i.e., only the final shadow price is presented. But in order to see the effectiveness of the distribution grid capacity market, Fig. 8 is presented. In this figure, one can note the convergent process of the shadow price in the second iteration of Fig. 7. During the time slot of 9 to 16, the total power demands from FO₁ and FO₂ are same, but the power capacity varies from 70 kW to 56 kW with a stepwise decrease of 2 kW. The result shows that the lower power capacity results in higher shadow price. Besides, the steady state is reached quickly.

C. Day-Ahead Congestion Settlements

The charging cost of FO₁ and FO₂ are compared from two time periods, one is the cost before congestion management, and another is the cost after congestion management. Table I presents the results which show that charging cost of each FO increase a lot. It indicates a shortage of the distribution capacity.

V. DISCUSSION AND CONCLUSION

In this paper, two control issues are integrated in a low voltage active distribution system consisting of three actors, DSO/Market operator, FO and EV owner. One is the optimal charging of EVs, another is the congestion management on the distribution system level. Two steps are adopted to address these two issues, linear programming is firstly used to model the charging process of EVs and to produce an aggregated energy schedule of FOs. If the sums of the energy schedule of

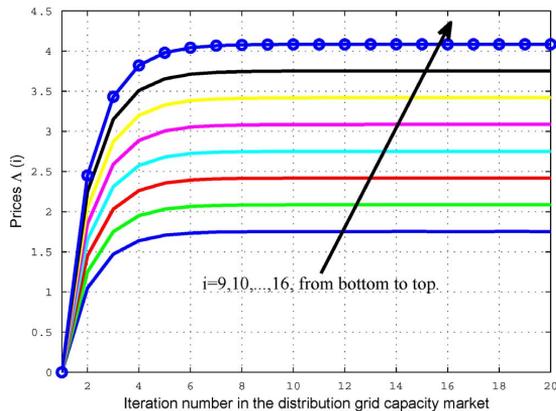


Fig. 8. Convergence of $\Lambda(i)$, $i = 9, 10, \dots, 16$ toward the shadow price in the second iteration of Fig. 7, the converged price in each time slot of this figure corresponds to the circled values in the Fig. 7(-to left).

TABLE I
CHARGING COST OF FOS IN THE PERIOD OF BEFORE AND AFTER CONGESTION MANAGEMENT

Fleet operator	Cost before congestion management	Cost of congestion prevention
FO_1	46.05 DKK	81.45 DKK
FO_2	46.46 DKK	86.72 DKK

the FOs overload the distribution grid, then, a distribution grid capacity market scheme is adopted to coordinate the energy schedule. The proposed solution for solving the congestion problem and managing the charging of EVs is an integration of a direct control and a price-based coordination. It is believed that the safety operation of the distribution grid can be highly ensured by coordinating the relation between the three market actors with the proposed framework. We also expect that such coordination strategy can be used to control other smart appliances, including thermostatically controlled loads such as heat pumps. As we discussed before, the market scheme can also be used in the real time for congestion relief.

We want to point out that voltage control is also an important issue for distribution grid operation, although we did not consider it in this study. In a practical way, in the planning period, DSO considers and pre-handles it by reinforcing the grid infrastructure based on the regulations already existed which describe the allowed voltage safety bands in the distribution grid. In the normal operation period, in the substation level, transformer has a tap change which can be used to regulate the voltage. Such as in Denmark, in general, 60 KV/10 KV transformer is an OLTC (On-load tap-changers). In the future, system operator could set up some grid codes for DERs, requiring the DERs to have their own embedded voltage control, which could solve the problem preventively. In the context of this study, voltage control can also be implemented by market scheme. This approach would be to establish a market where voltage stabilizing services can be bought or sold. Technically, it is feasible. However, it is not easy to identify and validate the committed power from the DERs, which will bring many challenges. Besides, the AC power flow calculation will also introduce time-consuming problem to this method. In a simple

market way, due to the increasing penetration of distributed generation, DSO can solve this problem by a contract-based solution, such as DSO can sign some contracts with FOs to get the required services.

It is noted that market approach has been well discussed and considered as one of the best approach for resource allocation, meanwhile, we also see some practical point deserve discussion for utilizing this approach for congestion management, mainly from three perspectives: 1) Stakeholder's acceptance on using price coordination: Although using price coordination approach would possibly enable an optimal resource allocation, but the uncertain in terms of end-user involvement, clear business models for FOs and DSOs, and the necessity for the regulatory support makes using price as a coordination tool for serving grid services a challenging task. 2) Size of the market and the associated market power issues: To ensure enough competition and fairness of the capacity market, one prerequisite is the number of market participants, i.e., FOs. If there are few FOs in the distribution area, issue e.g., market power will become a major challenge from the market perspective. 3) The information communicating between various stakeholders and the supporting ICT infrastructure: FOs need to communicate well with EVs in order to make an optimal charging schedule, these information include driving pattern, state of charge, some other preferences of EV owners. The time-stringent is not an essential issue here, however, EV owners cooperation are much wanted. For the interaction between FOs and distribution grid capacity market operator, real time communication is a challenge, but we can set up a reasonable time range and also try to limiting the market iteration with certain rules. This kind of setup will require advanced ICT infrastructure.

To sum up, the proposed method is flexible and scalable and can technically be enhanced to provide a complete set up for the congestion prevention in the scheduling period and congestion relief in real time, by taking into account the discussion above. Additional, the practical points discussed above imply the economic feasibility should also be analyzed in future.

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A.7 Multilevel coordination in smart grids for congestion management of distribution grid

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Multilevel Coordination in Smart Grids for Congestion Management of Distribution Grid

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Abstract—The operation of the distribution network will change in the near future due to increasing size and number of distributed energy resources (DER) and demand side resources (DSR). An active distribution network is proposed to address the challenges. The normal operation of an active distribution network requires coordination of different values and operation constraints of various involved actors. This paper proposes a multilevel coordination strategy for congestion management of distribution network. Firstly, the scheme of an active distribution network is described. Then, the coordination strategies between various actors, i.e., distribution system operator (DSO), fleet operators (FO), and EV owners are discussed. Further, a mathematical formulation of the chosen coordination strategies between DSO and FOs are presented and some case studies are shown to illustrate the effectiveness of the proposed solutions. Finally, we give the argument and proposal of using multi-agent based platform to demonstrate the multilevel coordination solution.

Index Terms—Congestion management, Distribution grid, Multilevel coordination, Multiagent systems based platform

I. INTRODUCTION

Denmark was a pioneer in wind power which provides a large amount of electricity to Danish consumers, at the end of 2012 [1], the total installed wind capacity in the Danish power grid was 4,162 MW which share 30% of the domestic electricity usage. Wind energy in Denmark is expected to grow due to the political strategy of 50% wind power in the 2020 Danish power system [2]. The total installed wind power in Denmark is connected at the distribution system level, which bring challenges to Energinet (TSO of Denmark). Energinet has limited or no access to the information about the state at the low grid voltage level. In order to address the challenges, several actions [3] have been implemented or planned, such as

- Coordinate the power flows among different systems by electrical interconnections, mostly high voltage direct current to the TSOs in the Sweden, Norway, Germany, and soon the Netherland.
- Balance the power system by the deregulated power market with the collaborations of power Balance Responsible Parties (BRP). The BRPs make the power and energy bids into the market, consists of conventional power and wind power.
- Implement a tool that provides real time estimation of the amount of injections from wind energy.

- Manage the flexible demand, like electric vehicles, heat pumps.

With the expected development towards a power system dependent on intermittent renewable energy sources, the need for some of the ancillary services is likely to increase, especially for balancing purposes. Both EVs and heat pumps are believed to play important roles in balancing the system. In order to aggregate the flexibilities of demand and capturing the business opportunities of providing the service to the system operator, a new business entity, namely fleet operator (FO) has recently emerged [4], [5]. Alternative names for an FO are virtual power plant (VPP), aggregator or charging service provider. However, the operation of the distribution grid may be challenged due to the increasing size and number of consumption units which can cause problems in peak hours. Besides, there exists facts that the closer the renewable production installed to the consumer premises and the consumer's awareness of consumption. As a result, the DSO have started to recognize the necessity for electricity distribution and operation evolving from the usual passive unidirectional flow network to an active distribution network [6].

In this paper, we consider a particular case combining EV charging cost minimization and distribution grid capacity management (active power transfer capacity). Previous studies [7]–[9] has shown that EVs can provide valuable services to the system operator, for example, during strong wind conditions, where the total wind power production capability becomes highly utilized, the need of maintaining balance between production and consumption might increase and can be provided by utilizing the controllable flexibilities of EVs. As a consequence the distribution system might become overloaded. Besides, the spot electricity price might become cheap when the wind power penetration is high. This will also further increase the consumption on the distribution grid side. In order to address the challenge, our study aims to answer how the values and operation constraints among the DSO, FOs and EVs can be coordinated within a market based platform sitting in an active distribution network.

The remainder of the paper is organized as follows: In section II, a general introduction regarding the operation of distribution network today and an active distribution network is given. Besides, the scheme of an active distribution network

is also presented. Section III mainly presents the coordination strategies between DSO and FOs, FOs and EV owners. Then a framework for design and method development for multilevel coordination is illustrated in section IV. A case study is given in section V to demonstrate the proposed method. Further, the proposal of using Multi-Agent Based Platform to demonstrate the multilevel active distribution systems are made in section VI. Finally, discussion and conclusions are made in section VII.

II. MULTI ACTOR SETTING, MULTILEVEL COORDINATION IN AN ACTIVE DISTRIBUTION NETWORK

A. Distribution network operation

1) *Distribution Network Operation Today*: DSO tasks in conventional system operation [10], are mostly focused on ‘off-line’ tasks related to asset management and maintenance during normal system conditions. The primary objective under emergency conditions is to organize restoration of the network as quickly as possible. Distribution systems today tend to be weakly monitored as compared to transmission grids, and controlled in a decentralized fashion on the basis of preconfigured local controls (e.g. by means of grid codes and protection settings).

The key operations of the DSO are:

- Grid dimensioning (incl. contingency planning and load curve estimation)
- Maintenance and outage related topology reconfiguration
- Adjustment of transformer taps
- Fuses and relay operation
- Fault-analysis and repair
- Logging events and standard management report
- Managing trouble call information and inform customers.

2) *Operation in an active distribution network*: To illustrate a future operation scenario with a higher level of automation, it is considered how the above operations can be extended with additional online- and data intensive acquisition. In order to identify and solve congestion problems, the DSO requires additional measurement equipment and/or technology enabling identification and anticipation of load patterns and grid ‘bottlenecks’.

Key Operations for DSO congestion management in an active distribution network would be:

- Demand forecasting
- Grid state estimation
- Online grid measurements
- Real-time intervention in case of unexpected deviations challenging grid reliability
- Meter data collection and aggregation

B. The scheme of an active distribution network with multi-actors, multilevel coordination

Fig. 1 shows the scheme of an active distribution network, in which four types of actors are loaded on different levels. In general, each of the actors is associated with a kind of operations, namely, the DSO is responsible for the reliability

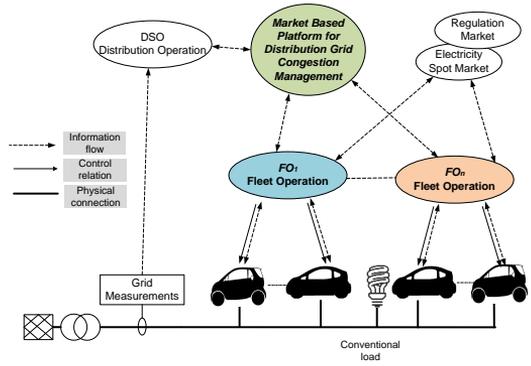


Fig. 1. Actors (stakeholders), problem domain and main information and control flows within an active distribution network.

of the distribution network, FOs are responsible for making the energy schedules, bidding it into traditional market such as day-ahead spot market and regulation market and providing the electricity for end users, EV owners are taking care of the charging of their EVs by subscribing to an FO or making the charging decision by themselves. By introducing a market based platform on the distribution grid level, the DSO will coordinate their requirements with market operator who then interact with FOs. About the control/coordination relations between FOs and EVs, this could be implemented either in direct control or indirect control method. Further discussion regarding the multilevel coordinations will be presented in next section.

III. COORDINATION METHOD AMONG THE VARIOUS LEVELS OF THE ACTIVE DISTRIBUTION SYSTEMS

A. Coordination method between DSO and FOs

Generally, the market based platform will be used to coordinate the requirements and values of DSO and FOs. The mechanism behind the market could be designed in many ways, such as various potential tariff regimes [11] [12], uniform price auction mechanism [13], shadow price based mechanism [14]. We briefly introduce three types of mechanisms in the below:

1) *Dynamical grid tariff*: In this method [12], the DSO generates a time and grid-location dependent price for grid usage based on expected nodal consumption levels. The DSO anticipates the size and the price-responsiveness of the load at critical grid nodes and calculates the price to optimally reflect the expected congestion problem. The FO will then get the dynamic nodal tariff and make an optimal schedule with respect to the predicted spot price and dynamic grid tariff.

2) *Uniform price auction mechanism*: The uniform price auction [13] can be designed as either single-sided auctions or two sided auctions. This will fully depends on the scale of the market, i.e., whether it is used by single DSO or multi DSOs supposing there are several FOs. It is noted that the uniform price auction mechanism is usually combined with

optimal power flow calculation, which mean either market operator/DSO will implement a lot of calculations.

3) *Shadow price based mechanism*: In this method [14], FOs will submit power requests to DSO for their aggregated energy/power schedule on each node (aggregated capacity) before submitting the energy schedule to the day-ahead market; in response they will receive a price for each node which reflects the respective congestion, and are requested to update their energy schedules. The process will terminate when all constraints are satisfied.

B. Coordination method between FOs and EV owners

Research in [15], [16] give a comprehensive review on the control strategies for flexibility aggregation. Three control architectures are examined and compared in [15], namely centralized load control, hierarchical load control via aggregators and distributed control. The control method is also discussed in [15], in which direct control and indirect control in the form of price signal are described. Direct control means that FO can direct schedule and control the charging of EVs [17]. Indirect control implies that FO coordinate the charging of EVs by either two way [18], [19] or one side price signals [20]. EV owner determine the charging profile of EVs by themselves. A short comparison between direct control and indirect control is given in Fig. 2.

	Control policies	
	Direct control	Indirect control
Features of the control policies	<ul style="list-style-type: none"> Control signals High level controller make the decision 	<ul style="list-style-type: none"> Price incentive Consumers make decision
Advantages	<ul style="list-style-type: none"> High certainty Better optimal results 	<ul style="list-style-type: none"> Privacy improved Less communication cost
Disadvantages	<ul style="list-style-type: none"> Sophisticated hardware High communication cost 	<ul style="list-style-type: none"> Lower certainty Demand Price elasticity is required

Fig. 2. Comparison between direct control and indirect control strategy

IV. FRAMEWORK DESIGN AND METHOD DEVELOPMENT FOR MULTILEVEL COORDINATION

Within the assumed system architecture, we propose a framework consisting of four fundamental stages [21], i.e., offline scheduling, online scheduling, real time control and settlement, to operate and control this system. These principles are in line with the system control function required at the control center of power system operation [10], i.e., instantaneous operation, operation planning and operation reporting. This framework is a fully charging profile management considering charging cost minimization and distribution grid capacity management. During the framework, shadow price based mechanism designed for the market and direct control between FOs and EV charging are used.

A. Framework design and method development for multilevel coordination

1) Energy schedule of the FOs without congestion management-Offline scheduling

All the FOs need to predict the energy requirements (driving patterns) of their customers (EV owners) and plan the corresponding expected charging schedule for the EVs. The methods of estimating the energy requirements and setting up the charging schedule may be different, but in general, the FOs try to minimize the charging cost of their customers as well as guarantee the driving requirements of the EV owners.

2) Market based approach for distribution grid congestion management-Offline scheduling

The market based platform will be used if congestion happens and the shadow price based mechanism is chosen for the market operation. FOs trade the power capacity of the distribution grid in this market. During the negotiation of the market, a shadow price will be issued by the market operator in the time slot where congestion happens. Then this shadow price will be sent to FOs, FOs will send back a new schedule to the Market operator, such iteration will be terminated until the congestion is eliminated.

3) Online scheduling and Real time control

It is valuable for FOs to utilize the online scheduling stage and make better charging schemes, especially regarding the participation in the regulating power market. Besides, if more accurate information is provided to the FOs, FOs can judge whether they need to reschedule the charging plan during this stage. With regard to real time control, one can assume that the EVs will charge according to the plan; however, if grid normal technical operation is compromised, FO management can be overridden by the DSO operation, such as using load shedding scheme.

4) Settlements

The settlements need to be designed well considering both the spot price and shadow prices. Besides, tax, transmission and distribution fees etc., should be taken into account.

B. Market based approach for distribution grid congestion management

In this subsection, we mainly focus on introducing the shadow price, where it comes from, how it can be utilized in the study.

1) *Analytical analysis of shadow price based market operation*: In general, the method starts with a proposed cost function which represents the cost of the power preference difference of a FO in each time slot, e.g.,

$$\mu_k = \zeta_k (\tilde{P}_{k,i}).$$

To facilitate the understanding, we assume

$$\mu_k = C_{k,i} (\tilde{P}_{k,i} - P_{k,i}^E)^2, \quad (1)$$

where k, i denote the index for the number of FOs and time slot in the scheduling period, $k = 1, \dots, N_B, i = 1, \dots, N_T$

$P_{k,i}^E$ means the schedule planned by FOs, $\tilde{P}_{k,i}$ denotes the control variable, $C_{k,i}$ means the weighting factor which are associated with the power difference, the larger $C_{k,i}$ implies a smaller difference.

The objective is to minimize the cost functions as well as respect to the constraint from DSO:

$$\text{minimize} \quad \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} (\tilde{P}_{k,i} - P_{k,i}^E)^2$$

subject to

$$\sum_{k=1}^{N_B} \tilde{P}_{k,i} \leq P_{Cap}(i), i = 1, \dots, N_T, \quad (2)$$

where $P_{Cap}(i)$ is the power capacity specifically for all the FOs, for example, it can be estimated by the DSO after deducting the conventional loads.

This problem is a convex optimization problem and relevant research [22], [23] show that by introducing Lagrange multipliers or shadow price $\Lambda(i) \in R^{N_T}$, problem (2) can be transferred into following partial Lagrangian problem:

$$L = \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} (\tilde{P}_{k,i} - P_{k,i}^E)^2 + \sum_{i=1}^{N_T} \Lambda(i) \left(\sum_{k=1}^{N_B} \tilde{P}_{k,i} - P_{Cap}(i) \right) \quad (3)$$

The centralized optimization problem (2) is transferred into a decentralized one with associated shadow price $\Lambda(i)$ in each time slot, with the purpose of emulating the market behavior. In our previous study [24], a strict mathematical proof is presented for the justification of the shadow price based mechanism.

2) *Cost and schedule adjustment algorithm within the market based platform:* The following steps illustrate the interactions among DSO, FOs, and market operator, cost adjustment algorithm and can mimic the trading and negotiation process in the market operation, when congestion happens.

(1) FOs submit their energy schedule to the DSO before submitting them to the electricity spot market.

(2) The DSO predicts whether congestion will happens based on the schedules of FOs, if happens, FOs need to go to the capacity market, otherwise, the energy schedule is approved.

(3) Capacity market operation

- FOs send their power schedule $P_{k,i}^E$ to market operator.
- Market operator determines the shadow price $\Lambda(i)$ and sends the price to FOs.
- FOs update their power schedule according to the shadow price and send it again to market operator.
- Such iteration will be terminated according to certain criteria, e.g., price convergence.

Intuitively, Fig. 3 illustrate the operation sequence.

V. NUMERICAL EXAMPLES

In this step, we will illustrate the effectiveness of utilizing the shadow price, i.e., $\Lambda(i)$ to facilitate the congestion

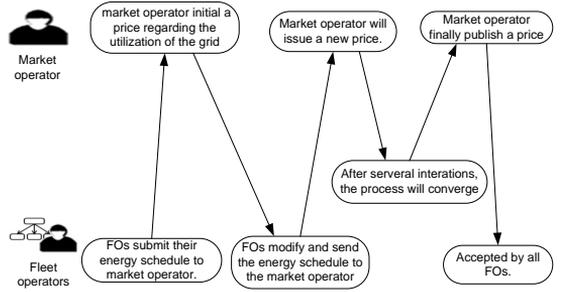


Fig. 3. Convergence of $\Lambda(i)$, $i = 9, 10, \dots, 16$ toward the shadow price.

management in the proposed method. It is noted that the cost function in this study presented by the quadratic function is assumed to represent the cost for the energy preference loss. The accuracy of the cost function is out of the scope of this study, the focus is to show how the FOs establish the schedule based on the cost function and the shadow price.

The weighting factor rate $C_{1,i}$, $C_{2,i}$ is set to 0.5 and 0.1. The value of α_ω is chosen as 0.1 in this case. Note that the variable $C_{k,i}$ and α_ω are connected, an appropriate value of the two variables can ensure smooth operation of the proposed method, i.e., the trade-off of the speed of the convergence and the accuracy of the solution. However, there is not a strict rule for choosing the parameter values. The power capacity $P_{cap}(i)$ is set up according to the trend in the real case; generally, the capacity is higher in the later evening and early morning time and lower in the day and evening time. Fig. 4 is presented to note the convergent process of the shadow price. During the time slot of 9 to 16 (15 minutes based time slot in a 24 hours time window), there exists congestion in the network, the total power demands from FO_1 and FO_2 are same in these time slot, (i.e., 39.1 kw from FO_1 and 41.4 kw from FO_2), but the capacity reserved for these time slot is 70kW. The result shows that the steady state is reached quickly. Note that each FO will obtain the final power schedule after the market operation. Because of page limitation, FO_1 's example is shown here, as presented in Fig. 5. From Fig. 5, one can see that the newly obtained power, i.e., the green curve is quite close to the blue curve, this is because FO_1 have higher weighting factor rate, which further imply that FO_2 will need to reduce a little more power comparing to FO_1 .

VI. GRID CONGESTION MANAGEMENT WITHIN A MULTI-AGENT SYSTEMS BASED PLATFORM

In the discussions above, it is observed that some general design principles are used such as decomposition, abstraction and scalability. These principles match the inherent capabilities of software agents and multiagent systems. In fact, multiagent system have been widely considered for control of power systems [25], starting from a low level control of devices to higher level of planning and optimization. A detailed explanation for the application of the three principles mentioned above

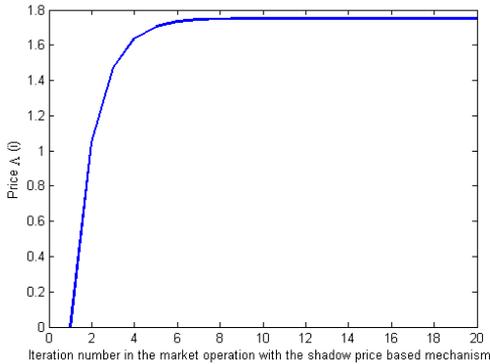


Fig. 4. Convergence of $\Lambda(i)$, $i = 9, 10, \dots, 16$ toward the shadow price.

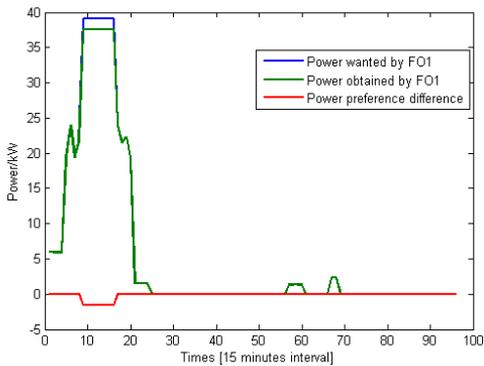


Fig. 5. Convergence of $\Lambda(i)$, $i = 9, 10, \dots, 16$ toward the shadow price.

is presented below:

- **Decomposition:** The electricity supply for the ender users is provided by several FOs. The congestion problems in a distribution network can be decomposed into subproblems, which the different DSO may face challenges on different levels of their grid. Some DSO might foresee problems on the medium voltage grid, while others may encounter potential problems with capacity in the low voltage transformers.
- **Abstraction:** Abstraction can be used to define a simplified model of the system that emphasizes some of the details or and suppresses others and to organize network operation. In this study, for example, FOs can be used to abstract the requirements and operations constraint of EV owners. In addition, the radial distribution grid can be abstracted in the form of Fig. 1 when emphasizing the active power transfer capacity management.
- **Scalability:** Multiagent systems have mature mechanism for implementation of cooperative and competitive mechanisms. These mechanism can be used in the interaction

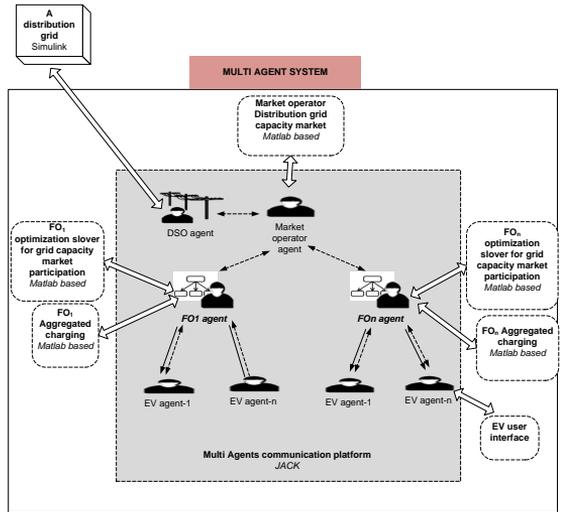


Fig. 6. Multiagent system based realization of the proposed scheme of an active power distribution network

of the market operator and the FOs. We will consider some competitive mechanisms between FOs in a future study because the above case studies mainly illustrate how the FOs can cooperate to mitigate the grid congestion problems.

According to the arguments above, we propose a multi-agent system architecture for the realization of the coordination of an active distribution network with multi-actors, as presented in Fig. 6. In which, all the agents will be built on JACK which is an agent-oriented development environment built on top of and fully integrated with the Java programming language [26]. JACK offers the environment and facilities message sending/receiving. Matlab based functions enables a declarative implementation of the decision module. Fig. 7 shows the skeleton of the agents in the JACK platform, in which three agents are presented, i.e., FO agent, DSO agent, Marketoperator agent. The envelope box represents the event that will be transferred between the agent. The rounded rectangle box means the plan that each agent has which will be used to handle the events. Basically, this skeleton illustrates the interactions between three agents intuitively.

VII. CONCLUSION

This paper primarily propose a framework for coordinating the values and operation constraints of various actors in an active distribution network. Multilevel coordination strategies are used in this study, i.e., price based platform is used to solve the congestion problems between DSO and FOs and direct control method are adopted to control the charging of EVs by FOs. We further give an argument that multi-agent based platform is suitable for the demonstration of the active distribution network with multi-actor setting, multilevel coordinations. A

A.8 A clearinghouse concept for distribution-level flexibility services

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A Clearinghouse Concept for Distribution-Level Flexibility Services

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Abstract—Flexibility resources on the demand side are anticipated to become a valuable asset for balancing renewable energy fluctuation as well as for reducing investment needs in distribution grids. To harvest this flexibility for distribution grids, flexibility services need to be defined that can be integrated with distribution grid operation and that provide a benefit that can be traded off against other grid investments. Two key challenges are here that the identification of useful services is still ongoing and that the transaction cost for the individually small contributions from the demand side could be prohibitive. This paper introduces a flexibility clearinghouse (FLECH) concept and isolates FLECH key functionality: to facilitate flexibility services in distribution grids by streamlining the relevant business interactions while keeping technical specifications open.

I. INTRODUCTION

Procuring system services from small distributed energy resources (DER), including flexible demand, has become a focus of research and field trials in recent years. The capability of managing DER via aggregators, to participate in bulk power markets as well as to provide system (ancillary) services has achieved much progress. Yet the provision of such services at distribution level has not seen the same development, either because they are simply uneconomic or possibly because market-based approaches are not easily introduced to distribution system operations.

A. Demand Response and Distribution Grid Planning and Operation

Two new drivers for increased grid demand are: 1) the development of renewables, in particular solar photovoltaic installations, and 2) the introduction of controllable and likely price responsive power consuming/producing units, including heat pumps and electric vehicles. These new units may cause grid issues such as voltage violations, reverse power flows, or thermal overloading. Such grid issues force distribution system operators (DSOs) to consider costly reinforcements while the effective grid utilization may actually be decreasing due to reduced diversity amongst the price responsive loads. Distribution grid planning and operation are conventionally focussed on planning and maintenance and are only slowly adopting “smart” approaches involving automation. The smart grid is suggested to enable better infrastructure utilization and the accommodation of additional generation and demand. One modern approach to increasing the effective hosting capacity

of distribution grids is to improve situational awareness for grid operators and planners through better feedback about the operating state [1].

Another approach is a better utilisation of demand side flexibility through new demand response programs, or ‘flexibility services’ [2]. Aggregating and controlling DER for commercial purposes is a field for new actors where technological and business innovation are essential for development. This development will either be facilitated or hampered by regulatory choices. The need for a regulatory framework for commercial flexibility services at the distribution level has been recognized, e.g. by the standardization mandate M490 and with the introduction of the traffic light concept [3], and is under development.

The introduction of new flexibility services at distribution level is thus a current and relevant concern, while, clearly, both the service definitions and the potential market-based coordination of such services are still largely open problems.

B. Congestion Management in Distribution Grids

At transmission level, congestion constraints are a common tool for reflecting transmission limitations toward market mechanisms, e.g. when interconnecting market areas. Congestion occurs when scheduled energy flows exceed the available transmission capacity [4]; congestion management is then the allocation of transfer capacity according to economic principles. Based on this definition, congestion can also be defined for distribution networks [5] as a coordination strategy reflecting operational constraints on market terms. A study in [5] analyzed three kinds of market mechanisms for alleviating congestion. In [6]–[8], prices are used to coordinate between DSO, aggregators and DER owners to achieve an optimal allocation, and in [9] different grid tariffs are discussed.

A simplification common in the distribution congestion literature [5]–[9] is to focus on ‘bottleneck’ constraints on a summation of power flows. This constraint can be interpreted as transformer current limit - for which there exists a business case on deferring grid investments. However, a DSO’s actual decision drivers and investment alternatives are often more varied and complex than the ones considered here, and regulatory requirements often inhibit the application of congestion constraints in distribution grids.

To achieve an incremental adoption and a better match of flexibility services with DSO regulations and procedures, DSOs should be enabled to request flexibility services adapted to actual practices of distribution system planners and to needs of flexibility service providers.

This paper introduces a concept which respects the practical requirements of a technically advancing DSO while opening the efficiency potential of market-based congestion management: the Flexibility Clearinghouse (FLECH). Following three key design principles, 1) to minimize transaction cost for DSO flexibility services; 2) to allow for further technical specifications of DSO services; and 3) to focus on business transactions and do not interfere with distribution operations, this concept has been developed and implemented within the Danish research and innovation project iPower: www.iPower-net.dk.

II. FLEXIBILITY SERVICES FOR DISTRIBUTION OPERATION

This Section defines the concept of a Flexibility Service, provides examples, and a framework for analysis.

A. Definition of a Flexibility Service

Many DER units have the capability of altering their generation/consumption pattern with limited impact on their primary energy service. This capability is further referred to as DER *flexibility*. Flexibility can be provided to a DSO through a new dedicated ancillary services market to which entities representing DER, here *Aggregators*, can submit bids. The products on this market are called *flexibility services* and include a detailed specification of the service *procurement, activation, delivery, validation and settlement*. These services include two generic types: (A) fully *scheduled* services which oblige the aggregator to behave as contracted without DSO intervention, and as well as (B) *reserve* services which entail a reserve or availability combined with a need-based activation by the DSO.

B. DSO Flexibility Service Examples

An analysis of relevant issues in the distribution system, reported in [2], identifies four key needs that could be fulfilled by flexibility services: response to foreseen and unexpected overloading, fast response to resolve N-1 situations, support in case of voltage limit violations (power quality), and support with respect to reactive power exchange with the transmission grid.

The same report, [2], suggests seven potential flexibility services to support the above needs. This paper will focus on those five services which offer flexibility via active power management:

- 1) *PowerCut Planned*: Used for handling predictable peak load for periodically daily issues in advance.
- 2) *PowerCut Urgent*: Used for handling peak loads on an event basis.
- 3) *Power Reserve*: Used when the system is operating in the reserve band of the feeder, and a fault in the system would require the utilization of the reserve band.

- 4) *PowerCap*: Activated upon request to ensure that the capacity limits specified by the DSO are not violated.
- 5) *PowerMax*: Same function as PowerCap, but activated through a planned schedule.

These services address the first two needs mentioned above, i.e. response to overloading and to N-1 situations. Notably, they include both fully *scheduled* products, i.e. (1) and (5), as well as *reserve* products, (2)-(4). As stipulated in [2], these service definitions are expected to be among the first ones accepted by DSOs. However, they do not constitute an exhaustive list of potential services.

C. A Framework for Analyzing Flexibility Services

In [5] an analysis framework of four stages for has been introduced: 1) *Offline Planning*, 2) *Online Scheduling*, 3) *Real-time Operation*, 4) *Offline Settlement*.

The framework is suited to identify alignment of technical and market functions across all participating actors. Key operations for each stage are listed in Table I.

TABLE I
STAGES OF SERVICE PROVISION AND ASSOCIATED FUNCTIONS

Stage	Market function	Technical function
Offline Planning	Contract specification and cost allocation	Grid planning and service specification
Online Scheduling	Contracting and resource allocation	Scheduling and reservation
Real-time Operation	Contractual fulfillment	Plan execution and activation/response
Offline Settlement	Financial settlement	Service validation

The stages and the separation of market and technical operations define a framework suited for the analysis of flexibility services and isolation of FLECH functionality.

III. THE FLEXIBILITY CLEARINGHOUSE CONCEPT

As described in [2], the FLECH is meant to facilitate DSOs to announce services and aggregators to bid upon. Here, the stakeholder setting and FLECH core functions are identified.

A. Stakeholder Roles and Need for a Flexibility Clearinghouse

Demand for system services from DER units exist all the way down to the low voltage grid. We identify associated interests with respect to the following conventional stakeholders:

- Transmission System Operator (TSO)
- Distribution System Operators (DSOs)
- Balance Responsible Parties (BRP)

New stakeholders in the context of DER services include:

- DER owners
- Aggregators

All stakeholders have interests of their own that require alignment to enable successful delivery of flexibility of flexibility services to a DSO. The DER owner is interested in offering flexibility which does not negatively influence the primary function of the unit. This flexibility will be defined in contracts between the DER owner and an Aggregator.

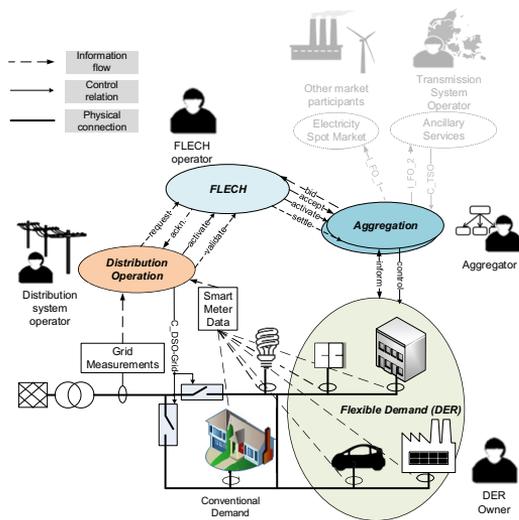


Fig. 1. Schematic overview of the considered actors and their roles in relation to the FLECH.

Depending on the capabilities of a particular DER unit, it may be able to offer system services to more than one interested party. For example, a controlled decrease in consumption could either be part of a frequency control service offered to a TSO, or it may be offered to a DSO for peak shaving. In any case, the invocation of the service would impact both grid domains, and the interests of TSO and DSO could conflict. In the present electricity market regulation, larger DER units interact with a TSO through a BRP. The business model of a BRP adds another set of interests which do not automatically align with the requirements of grid operation.

Two present ways of addressing flexibility services are grid codes and bilateral contracts. Grid codes are primarily suited to define absolute limits of operation. They have to be rigid as their scope is universal to all grid connected devices. The creation and updating of grid codes is a slow process which is not very innovation friendly and does not imply any remuneration. Individually negotiated bilateral contracts, on the other hand, imply a high transaction cost, which makes them unsuitable for services with small economic margins.

This setting illustrates the need for a service-independent and open platform for the arbitration of interests between the stakeholders involved in delivering a power system service from flexible DER units. The scope of this platform should be limited to providing an infrastructure on top of which the business logic of present and future services can be defined.

B. Functions of FLECH

A clearinghouse is a safeguard for a marketplace, ensuring the secure fulfilment of a business transaction. FLECH provides the platform for such transactions with respect to smart

services in the interest of a distribution system operator.

The FLECH concept is realized as a service-oriented platform that facilitates the business process of *specifying, contracting, delivery* and *settlement* of DER flexibility services. It requires involvement of a software provider. For operation, a new neutral stakeholder, similar to the role of a market operator for the bulk electricity markets, should be introduced.

The capability of FLECH will evolve with the development of distribution level markets. Initially, market clearing can be performed by the DSO. The FLECH functionality would mainly consist of bookkeeping and communication/broadcasting functions. In the future, when market mechanisms are more stable and services well-defined, market clearing would be implemented on the FLECH platform. Another optional functionality is a coordination role in the scheduling phase. None of the specified services in [2] require such functionality as it is allocated to DSO and Aggregators internally. For future congestion management strategies, such as reported in [5], online coordination of several aggregators would theoretically be more economically efficient.

During operation, two alternative service types – *reserve* and *scheduled* – need to be distinguished. To avoid technical real-time requirements for FLECH, the activation of reserve services should be sent directly to the respective aggregator, while FLECH assumes a pure bookkeeping role.

Finally, FLECH supports service validation and settlement. As all records of activations are available, FLECH can match bids and fulfillment and calculate the final settlement.

IV. FLECH INTERACTIONS

The FLECH functionality outlined above aims to facilitate interactions between DSO and flexibility service providers; this section identifies the required interactions and isolates the common message exchange requirements.

A. Flexibility Service Mapping

The framework introduced in Section II-C is used to map out the FLECH interactions for the candidate flexibility services summarized in Section II-B. Here, two services, *PowerCut Urgent* and *PowerMax*, are chosen as representative cases and their mapping is summarized in Tables II and III.

TABLE II
POWERCUT URGENT

Stage	Market function	Technical function
Offline Planning	Specification and announcement of reserve contract	DSO: identify location and volume of reserve need
Online Scheduling	(optional: call for short term bids to activation market)	DSO: Anticipate 'urgent' activation need time
Real-time Operation	–	DSO: Activation signal; DER respond within 15min
Offline Settlement	Payment per activation. Failure to deliver 4 times terminates contract.	Recording and validation of activation signal and response

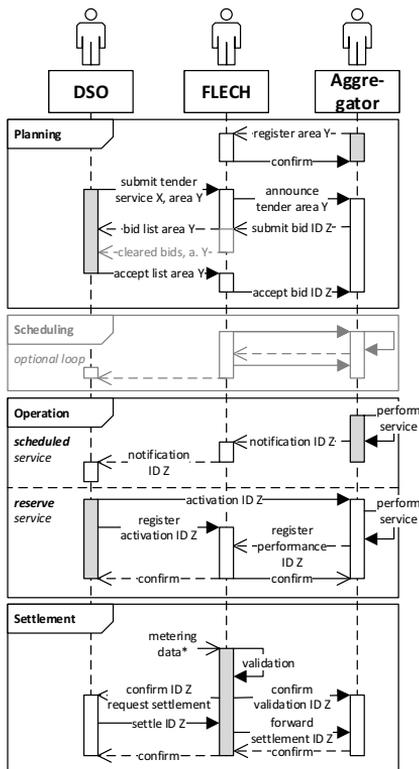


Fig. 2. Sequence diagram for FLECH communication

TABLE III
POWERMAX

Stage	Market function	Technical function
Offline Planning	Announce service request	Identify activation location, periods and volume
Online Scheduling	(optional coordination)	(DER and Aggregator: prediction)
Real-time Operation	-	DSO: monitoring only; Aggregator coordinates DER
Offline Settlement	Payment defined in the contract. Failure to deliver 4 times terminates contract	Recording and validation of activation signal and response

The following conclusions can be drawn from the analysis: At the *planning stage*, tender announcement and reserve agreements with a long lead-time are arranged, e.g. 2 - 6 months before activation. The *scheduling phase* is optional, yet valuable in a competitive setting: due to short lead time (e.g. 1 - 24h ahead) bid prices would improve due to reduced uncertainty. At the *operation stage*, the services can be differentiated into *reserve* and *scheduled* services. For scheduled services a simple notification of activation will be performed. For reserve

services, the DSO will send an activation signal directly to the aggregator. FLECH must be notified if the activation is executed. The notifications are used for settlement. With regards to *offline settlement*, FLECH will be the responsible for coordinating validation, consolidating the judgment from different actors.

B. Generic FLECH Messages

The FLECH key interfaces are to DSO and Aggregator. The sequence diagram in Figure 2 summarizes the essential message flow, grouped by stage. Focussing on the transactional, administrative, aspects of service provision, the key interactions are common to all services considered, with two exceptions: the scheduling stage would depend on the respective service and market clearing model, and in the operation stage, separate sequences are defined for scheduled and reserve services. The adoption of new services to the a first FLECH design will therefore come at a small incremental cost.

V. CASE STUDY

This case study illustrates the application of the *PowerMax* service by a DSO in case of an anticipated low voltage transformer overload. Consider the following scenario:

(A) 70 household consumers are connected to a 10/0.4kV transformer T1, each with connection capacity of approximately $7kW$; an electric vehicle (EV) with up to $3.7kW$ charging capacity, [10], is associated with 14 of the households.

(B) Aggregators managing controllable consumption in this grid area are two EV fleet operators, FO1 and FO2. FO1 operates 5 EVs and FO2 9 EVs, corresponding to $18.5kW$ and $33.3kW$ charging capacity, respectively.

(C) Based on historical data and specific load models, the DSO anticipates that the $175kW$ limit (corresponding to 70% of the maximum $250kW$) of transformer T1, may be exceeded by $37.8kW$ on weekdays between 4:30pm and 8:00pm during the months of December, January and February, mainly caused by additional EV charging loads; the corresponding load profile is illustrated in Figure 3.

(D) The DSO has the option to reinforce the transformer or to acquire a flexibility service. An economical evaluation suggests that flexibility services could postpone reinforcement and thus are an attractive option. Due to the characteristics of EV loads, the *PowerMax* service is chosen as most viable.

To prepare the FLECH tender, the DSO identifies its needs: having 14 EVs with flexible consumption in the area charging at maximum rate, the peak load of the EVs is $51.8kW$ – under current Danish regulations, the only capacity limit is the physical connection capacity. The DSO thus needs to reduce, for the given time window, this maximum capacity limit to $14kW$, i.e. the total capacity of the two aggregators should be reduced by $37.8kW$. With *PowerMax*, the DSO therefore requests a reduction against documented connection capacity of the aggregators in the area. Apart from announcing the quantity to be reduced, the DSO includes a ‘recommended’ rate in order to initiate price discovery.

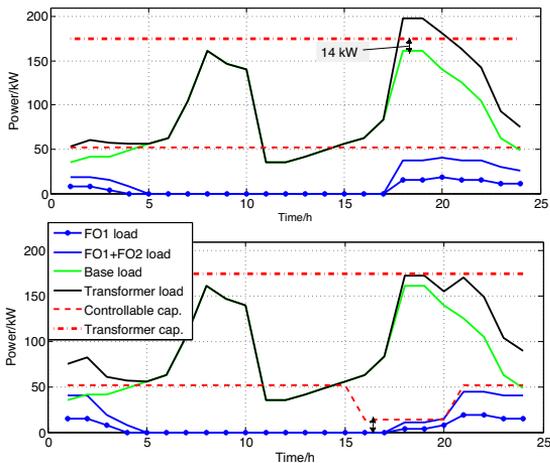


Fig. 3. Expected load profiles for days with anticipated feeder overload. Top: Expected profile before PowerMax tender. Bottom: Expected profile after PowerMax tender.

In this scenario, FLECH facilitates the tender and transactions associated with the service provision. The individual steps are related to Figure 2. At the *planning* stage, the DSO submits the following service tender to FLECH:

PowerMax:

CAPACITY REDUCTION [AREA T1]: 37.8kW

TIME 4:30pm TO 8:00pm ON weekdays

PERIOD 01 Dec 2014 TO 28 Feb 2015

RECOMMENDED RATE 500 EUR/kW

This tender is then announced by FLECH to all aggregators registered for T1. The aggregators bid into the FLECH:

AggID [BidID]: reduction FROM capacity AT rate flex?

FO1[FO1B1]: 12.3kW FROM 14.8kW AT 500 EUR/kW FULL

FO2[FO2B1]: 12.3kW FROM 14.8kW AT 700 EUR/kW FULL

FO2[FO2B2]: 15.4kW FROM 18.5kW 1000 EUR/kW FLEX

Note that FO1 did not bid with all of its resources, effectively only using 4 out of 5 cars, and that the second bid by FO2 is FLEX bid, i.e. it does not need to be accepted entirely. After gate closure their bids are forwarded to the DSO which evaluates the offers and decides to accept the following bids:

BidID: FO1B1, FO2B1, FO2B2*90% AT 1000 EUR/kW

This leads to an effective capacity reduction of 38.5kW which fulfills the required 37.8kW. The prices of this case study are completely fictitious and not anchored in real costs.

As the *PowerMax* service includes a schedule, aggregators determine their commitment internally and no interaction is required at the *online scheduling* stage. At the *operation* stage FLECH collects the activation notifications which are passed on to the DSO to verify the performance. At the *settlement* stage, the Metering Responsible submits metering data to FLECH and FLECH validates the performance. The settlement transaction is facilitated by FLECH.

VI. CONCLUSION

This paper presented a clearinghouse concept for facilitating ancillary services at the DSO level. With the emergence of new players in DSO ancillary service markets, it is foreseen that such a mechanism will be needed to minimize transaction costs. In contrast to other contributions on distribution congestion mitigation, the FLECH adapts to the actual DSO needs and is not tied to a specific aggregator architecture.

Two representative flexibility services have been chosen to identify the FLECH requirements. By separating market and technical aspects of the services, it is possible to isolate the need for a pure market facilitator, which either facilitates bilateral contracts or operates a market-clearing facility.

The role of FLECH and its interactions with stakeholders of the distribution flexibility service market have been described. A case study has been presented showing how FLECH is envisioned to work in a concrete scenario.

Several important aspects of flexibility services have been out of the scope of this paper and will be addressed in future work: (A) A flexibility service requires the formulation of a ‘baseline’. This baseline at transmission level is based on the energy markets, but there is no such formal baseline at the distribution level for DER. (B) The activation of flexibility services may potentially cause an imbalance cost. It is not clear to which actor this cost should be allocated. (C) The aggregator is assumed to be an independent entity representing the DER towards FLECH and the DSO. This assumption is currently not backed up by regulation, partly because of the imbalance issue noted in point (B).

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A.9 A multi-agent system for distribution grid congestion management with electric vehicles

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A multi-agent system for distribution grid congestion management with electric vehicles

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Abstract

Distributed energy resources, like electric vehicles (EVs) are widely regarded as valuable assets in the smart grid in addition to their primary transport function. However, connecting EVs to the distribution network and recharging the EV battery without any control may overload the transformers and cables in peak hours when EVs's penetration is relatively high. In this study, a distributed control strategy for integrating EVs into the distribution network is proposed to coordinate the self interests and operational constraints of two actors: the EV owner and the Distribution system operator (DSO), facilitated by the introduction of fleet operator (FO) and grid capacity market operator (CMO). The control strategy includes control system design and distributed control algorithm development which is based on general equilibrium market mechanisms. In order to fully demonstrate the coordination behavior inside the proposed strategy, we build a multi-agent system (MAS) which is based on the co-simulation environment of JACK and Matlab. A use case of the MAS and the results of running the system are presented to intuitively illustrate the effectiveness of the proposed solutions.

Keywords: Congestion management, Distribution grid, Electric vehicles, Multi-agent system, Resource allocation.

1. Introduction

EV is widely advocated as a mean of personal transport and urban delivery, since it can contribute to the reduction of CO₂ emission, especially when the recharging electricity is generated by renewable resources. However, for the electric utilities, the issue is how to integrate the EVs smoothly into the grid, i.e., manage the simultaneous charging of a large scale of EVs, without overloading the grid. Several studies (Heydt, 1983; Lopes et al., 2011; Clement-Nyns et al., 2010; Green II et al., 2011) have shown that uncontrolled charging (alternatively is called dumb charging) of EVs will challenge the capacity of the distribution grid. To address this challenges, the time-of-use tariffs or multiple tariffs charging scheme are used in the early stage to relieve the congestions in the peak hours (Shao et al., 2010). But using tariffs solely are not adequate to eliminate the congestion, since they would shift peak load to its neighbouring period (Ma et al., 2013; Karfopoulos and Hatzigryriou, 2013).

Recently, much research has been aiming to coordinate the objectives and the constraints centrally, e.g., to optimize the charging cost of EVs as well as respecting the hard constraints imposed by EV owner needs and distribution grid operation. In (Sundstrom and Binding, 2012), a complex scheduling problem involving the EV owners, the fleet operator (FO) and the DSO is analyzed. The approach requires a complex interaction between the DSO and the FO, on each interaction, the FO will get a spe-

cific grid constraint from the DSO and add it into the EV charging cost minimization problem. The results show that both the FO and the EV owners can achieve the objectives of minimizing charging costs and fulfilling driving requirements without violating the grid constraints. Lopes et al. (Lopes et al., 2009) proposed a conceptual framework consisting of both a technical grid operation strategy and a market environment to integrate EVs into the distribution systems. The FO is proposed to manage the EVs and the FOs will prepare the buy/sell bids into the electricity market. Having this defined, a prior interaction with the DSO must exist to prevent the occurrence of congestion and voltage problem in the distribution network. The smart charging algorithm is mainly designed for the operation of the DSO which can maximize the density of the EV deployment into the grid. It is also assumed that the grid has enough capacity to provide all the power required by EVs. With this assumption, the centrally smart charging approach is effective.

Although these proposed solutions are shown to work efficiently for a limited number of EVs, centralized management requires the acquisition and processing of an enormous of information for a large penetration of EVs, such as: 1) the battery model of EVs, initial state of charge (SOC) and desired SOC of EVs; 2) driving pattern of EVs; 3) grid constraint information from DSO; 4) electricity market information, which would substantially request significant computational resources, communication overheads and communication infrastructure cost. Research in (Lyon et al., 2012) indicates that the benefits for the centralized charging management might not be justified for the communication infrastructure cost. Alternatively, several ways of solving the congestion problem in the distribution grid have been suggested from market perspective. In (Andersen et al.,

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2012), the paper conceptualizes several approaches, i.e., distribution grid capacity market, dynamic grid tariff (O'Connell et al., 2011), to address the distribution grid congestion. The conceptualized strategies for congestion management are evaluated in terms of their complexity of implementation, the value and benefits they can offer as well as possible drawbacks and risks. Further on, the work in (Hu et al., 2013) analyzed the shadow price based grid capacity market scheme, in which, FOs centrally schedule and control the charging of EVs, they negotiate with the market operator (distribution grid capacity market) on the limited capacity of the distribution grid if it is needed. The focus of the study (Hu et al., 2013) is the mathematical proof of the proposed market scheme. Some numerical case studies are shown to illustrate the effectiveness of the proposed solution.

To implement and assess both control strategies of smart charging of EVs, especially market based coordination method, a multi-agent system (MAS) based technology is very suitable (Jennings and Bussmann, 2003), which can be justified by the following reasons:

- The increase in complexity and size of the whole EV charging network bring up the need for distributed intelligence and local solution, which fall into the scope of MAS based technology.
- The information flow, optimizations and the negotiations happened in the smart charging network of EVs can be well demonstrated and integrated into a MAS.
- The system can be pre-tested and pre-analyzed by using a MAS before going to real implementation.

In addition to these general arguments, MAS has been widely proposed in the context of power systems, such as power system restoration (Nagata and Sasaki, 2002), power system operation and control (Rehtanz, 2003). More recently, the multi-agent concept is proposed for distribution system operation and control (Nordman and Lehtonen, 2005; Issicaba et al.; Pipatanasomporn et al., 2009; Ren et al., 2013), especially, considering the capacity management with a large population of electric vehicles (Karfopoulos and Hatzigiorgiou, 2013; Miranda et al., 2011) and the capacity management with more general loads (Greunsvan et al., 2012). The authors (Karfopoulos and Hatzigiorgiou, 2013) proposed a distributed, multi-agent EV charging control method based on Nash certainty equivalence principle that considers distribution network impacts. Four types of agents are included in the study, EV aggregator agent, regional aggregation agent, microgrid aggregation agent and cluster of vehicles controller agent, and vehicle controller agents. In the non-cooperative, dynamic game, all the vehicles controller agents decide the strategy that minimizes his own objective functions. The up-level agents coordinate vehicles controller agents' charging behaviour by altering the price signal. The price signal is a reflection of congestion conditions. The results indicated that the proposed approach allocates EV energy requirements efficiently during off-peak hours which achieves effectively valley filling and also leads to maximization of load

factor and minimization of energy losses. The authors in (Miranda et al., 2011) used the MAS to design a distributed, modular, coordinated and collaborative intelligent charging network with the objective of pro-actively scheduling the charging of up to fifty EVs as well as eliminating the grid overloading issue. The study mainly considered how the electricity is distributed to the multiple charging point agent under one local power manager agent and this is done by an auction mechanism. Each charging point agent makes a bid for the energy in the next 15 minutes until it get the desired state of charge of the battery, then the local power manager agent sorts out the orders to determine which EV can be charged during the time slot. In (Greunsvan et al., 2012), an active distribution network (ADN) is presented with its actors and their objectives. The multi-agent technology is proposed for the normal operation of the ADN, in which the auctioneer agent (placed at the MV/LV transformer) communicates with the device agent by sending the price signal and receiving the bid curve. Further on, capacity management is investigated by transforming the bid curves of the device agents.

This paper is an extension of the concepts described in (Hu et al., 2013). The extension mainly utilize the MAS technology to assess the proposed market scheme with the purpose of illustrating and tracking the coordination behaviors. Moreover, the extension considers demonstrating EVs' flexibility (through the presence of response weighting factor to the shadow price) in the developed MAS system. There are several highlights in this study compared to previous studies (Karfopoulos and Hatzigiorgiou, 2013; Miranda et al., 2011; Greunsvan et al., 2012).

- The developed MAS offers a modeling environment that enables study of important characteristics of the proposed distribution grid capacity market which is not presently available. By implementing and assessing the market based strategy, it is shown that grid congestion problem can be eliminated in few steps.
- The developed MAS explicitly presents the relevant agents, the plan, and the event inside a market frame. The modelling approach can be an example for other similar problems.
- The developed MAS demonstrates a simulation platform which is based on the integration of JACK and Matlab. The platform can well integrate the advanced optimization and control and the interactions which can vary from simple information passing to rich social interactions such as coordination, negotiation.

The remainder of the paper is organized as follows: In section II, an introduction is given on the assumptions and control system architecture. Section III mainly presents the mathematical principles behind the methods of smart charging of EVs and distribution grid congestion management. In section IV, MAS based realization of congestion management scheme is presented. Case studies are illustrated in section V to facilitate the understanding. Finally, discussion and conclusions are presented in section VI.

2. Control system architecture

2.1. Main actors in the control system

Typically, the challenges in the distribution grid caused by the increasing electricity consumption from EVs and heat pumps (Søndergren, 2011) are solved by expanding the grid to fit the size and the pattern of demand. As an alternative, inspired by the congestion management method at the transmission system level, it is then defined in this study that the capacity of the distribution network (scarce resources) is allocated according to economic principles without upgrading the grid.

Fig.1.(a) presents a sketch of a typical situation in a distribution network where the substation supports the electricity to the households connected to it. In this distribution network, it is assumed that the consumers own controllable appliances, i.e., EVs, besides some conventional loads. These EVs have contracts with the FOs who are the new entities in a smart grid environment. FO has been widely proposed to provide the charge services to EVs and it is further assumed that the FO is also responsible for managing the EV charging infrastructures, i.e., the EV supply equipment (EVSE) (Bessa and Matos, 2012; San Román et al., 2011). As illustrated in Fig.1.(b), EVSE supports the smart charging functions. The decision can be made on the EV level or on the FOs level. The IEC 15118 is the most recommended communication standard and demonstrated in details in (Kabisch et al., 2010; Schmutzler and Wietfeld, 2010) by showing the sequence diagram of a charging process between the EVSE and the EVs. For the communication between the EVSE and the FOs, it is recommended that IEC 61850 can fulfil the functions. We use EV_i as an agent to represent the EV owner's operation on EVs and it will communicate with the FOs. In this study, it is assumed that the DSO will coordinate with the FOs to alter the EV's charging profile to prevent/eliminate the overloading problem. The coordination between the DSO and the FOs is facilitated by the grid capacity market operator. In the following section, some market based coordination methods will be discussed for the interaction between the DSO and the FOs.

2.2. Coordination relationships between the actors in the control system

2.2.1. Allocating the available power of DSO among the FOs by standard price-oriented market protocols

As discussed in (Akkermans et al., 2004; Wellman, 1993; Cheng and Wellman, 1998), market-based control method is very efficient and applicable for handling the resource allocation problem. The authors (Akkermans et al., 2004) discussed the theoretical foundations of distributed large-scale control problem by unifying the microeconomics and control engineering in an agent-based framework. One of the main results of this study is that computational economies with dynamic pricing mechanisms are able to handle scarce resources for control adaptively in ways that are optimal locally as well as globally. It is further recommended in the study (Akkermans et al., 2004) that standard price-oriented market protocol, e.g., Wellman's WALRAS algorithm (Wellman, 1993; Cheng and Well-

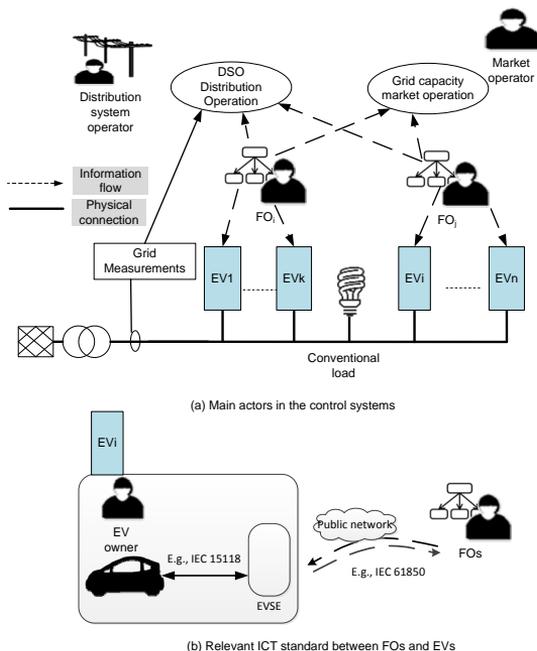


Figure 1: A illustration of distribution network with EVs.

man, 1998) is suitable for implementing the agent-based microeconomic control. The algorithm presumes an auctioneer agent which announce the market clearing price p and the control agents will submit their demand γ_α based on the price, then the auctioneer agent updates the price until the equilibrium value is found. The market-based approach has been supported to be used in the power distribution system, such as the discussion in joint research center European Forum¹ or in the research (Nordentoft, 2013; Schlosser, 2010; Lorenz et al., 2009).

2.2.2. Coordination method between FOs and EV owners

The control method between the FO and the EVs developed in (Sundstrom and Binding, 2012; Lopes et al., 2009; Hu et al., 2013) belongs to centralized control strategy, while the one developed in (Ma et al., 2013; Karfopoulos and Hatzigryiou, 2013) goes for distributed control. Studies in (Karfopoulos and Hatzigryiou, 2013; Richardson et al., 2012) compared the centralized control and distributed control method when utilizing them to make an optimal plan which can optimally delivery energy to EVs as well as avoiding grid congestions. They outlined the advantages and disadvantages of both strategies.

¹European commission Joint research centre, Scientific support to capacity markets and the integration of renewables, Brussels (BE) - 22/07/13

2.3. Distribution grid congestion management with EV integration

Shadow price protocols are proposed for the coordination between the DSO and the FOs agent in (Hu et al., 2013), in which the shadow price used as a market clearing price is updated in each bidding round by the grid capacity market operator (served for the DSO). The bids is coming from FOs which represent the EVs and directly schedule and control the charging of EVs. In this study, we modify the coordination method between the FOs and the EVs by distributing the charging decision to the EV agent. A response weighting factor to the shadow price is introduced to the individual EV agent. With this presence, the EV agent can show their willingness to charge or not during the higher price time slot.

In the following section, a distributed method is proposed for integrating the EVs into the power distribution systems. Fig. 2 shows the steps of the proposed methods:

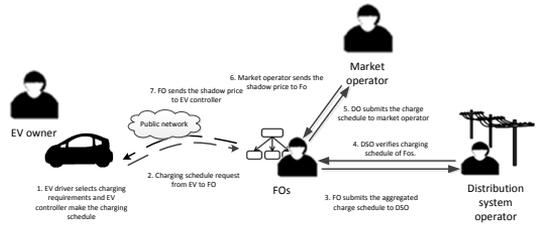


Figure 2: Scheme of the proposed solutions

1. The EV owner selects charging requirements and EV controller generate the charging schedule, e.g., based on charging least cost strategy, dumb charging strategy etc.
2. The EV owner sends the charging schedule to the FO which they have been subscribed.
3. The FOs aggregate the charging schedule from their contracted EV owners and submit the aggregated charging schedule to the DSO.
4. The DSO verifies the charging schedule of FOs by running load flow calculation and sends the results to all the FOs.
5. The FOs submits the charging schedule to the Market operator if there exists congestions; otherwise, the FOs could bid the energy schedule to the energy spot market and the procedure stops in this step.
6. The Market operator sends the shadow price to the FOs and the FOs resubmits the charging schedule to the Market operator until the shadow price is converged.
7. The FOs sends the shadow price to all the EV controllers.
8. Repeat the step 1 to step 7 until the congestion is totally eliminated in the planning period.
9. Bid final energy/power schedule to the electricity spot market.

The key concept is that the FOs/EVs' energy schedules are coordinated by the DSO/Market operator before they are sent to the energy market.

2.4. Further discussion on the proposed method

With the purpose of further illustrating the proposed distribution grid capacity market, we give some basic introduction to the congestion management method and the markets, i.e., Spot market and Regulating power market, operated at the transmission system level. Three very different methods of managing the congestion of the transmission system in the deregulated environment, have been presented in (Christie et al., 2000). The three methods are the optimal power flow model used in the United Kingdom, Australia, New Zealand, and some part of the United States, the price area based model used in the Nord-Pool market area in Nordic countries and the transaction based

model used in the United States. In Spot market, the Power Balance Responsible parties (PBRs) make the power and energy bids into the market, consists of conventional power and wind power. With the trading, they can balance the power systems in the deregulated environment. As electricity production and consumption always have to be in equilibrium, deviations in the operating hours are left for the transmission system operator (TSO) to balance which is done via the regulating power market. Note that the dispatch currently is set only based on the spot market and the operational state of the distribution grid is not considered. In short, the proposed solution of this study can enable the distribution congestion management before the operation of the dispatch. And the capacity market we proposed only takes place when it is required, i.e., in the situation of possible congestions predicted by the DSO.

Besides, we have made some assumptions that FOs fully cooperate in the grid capacity market to avoid the congestion issue. This assumption is made based on the discussions in (McCalley et al., 2003; Raiffa, 1982), in which, three types of negotiations have been characterized as either strident antagonist, cooperative antagonist or fully cooperative. The first one means the agents are complete distrust each other. The latter means the agent are entirely self-interested but ones that recognize and abide by whatever rules exist. The third type means the agents perform no strategic posturing and think of themselves as a cohesive entity with intension to arrive the best decision for the entity, although they have different needs, values, etc. By being fully cooperative in our context, FOs will honestly submit the bids based on their marginal cost functions and the impartial market operator will update the market clearing price only reflecting the constrained resources (distribution grid capacity).

Lastly, in this shadow price mechanism based method, FO, EV owner needs to pay the higher shadow price if they charge the EVs in the time slot where congestion happens and DSO seems cost nothing to eliminate the grid congestion. However, in the real practices, it is the DSO's responsibility to upgrade the network to address the challenges. It is therefore assumed that the shadow price can be modified when sending to the FOs or the FOs may get compensation from the DSO. In addition to this, DSO need to support the operation of the market operator and can investigate the saving on the information and communication infrastructures in the distribution grid.

3. Problem formulation and control algorithms development for EV charging schedule generation and grid congestion management

In this section, we firstly introduce the newly defined method for the EV charging schedule generation, then summarize the key elements of the mathematical formula part of our previous work (Hu et al., 2013), i.e., the algorithm for shadow price based coordination.

3.1. EV charging schedule generation

Linear programming is used and modified to model the charging process of EVs (Hu et al., 2013, 2011). The objective is to minimize the charging cost as well as fulfilling the driving requirement of the EV owner. The scheduling period is divided into N_T time slot and the time slot could be hourly based or fifteen/ten minutes based depending on the modeling requirements. The objective function is defined as the product of virtual price (predicted electricity price and the weighted shadow price, in which the shadow price reflect the congestion cost of the distribution grid) and a decision variable P_{ji} , where $j = 1, 2, \dots, N_k^E$ is the index for the number of EVs under one FO, N_k^E denotes the number of EVs under FO k . $i = 1, 2, \dots, N_T$ is the index for the time slot in the scheduling period. The physical meaning of the decision variable P_{ji} is to make a decision to distributed/charge the power on the certain time slots, where the charging cost can be minimized. Predicted electricity price is assumed to be known in each time slot. With the defined objective function and the constraints such as: 1) the available energy in the battery should be greater than or equal to the energy requirement for the next trip/time slot. 2) the available energy in the battery should be less than or equal to the power capacity of the battery. 3) The charging rate should less than or equal to its maximum power rate of the charger, the mathematical model of the solution is presented as follows:

$$\text{minimize} \quad \sum_{j=1}^{N_k^E} (\Phi_{ji} + \xi_i * \Lambda(i)) P_{ji} t, j = 1, \dots, N_k^E$$

subject to

$$\begin{cases} SOC_{0,j} + \sum_{i=1}^{N_T} P_{ji} t_{ji} \geq SOC_{Min,j} + \sum_{i=0}^{N_T-1} E_{drive,i+1} \\ SOC_{0,j} + \sum_{i=1}^{N_T} P_{ji} t_{ji} \leq w * E_{cap,j} + \sum_{i=2}^{N_T+1} E_{drive,i-1} \\ 0 \leq P_{ji} t_{ji} \leq E_{max,j}, i = 1, \dots, N_T \end{cases} \quad (1)$$

where Φ_{ji} means predicted day-ahead electricity market price vector, $\Lambda(i)$ represents the shadow price, ξ_i denotes the responding weighting factor the shadow price, t means length of each time slot. $SOC_{0,j}$ denotes the initial SOC of individual EV. $SOC_{Min,j}$ denotes the recommended minimum SOC of the EV. E_{drive} means the predicted individual EV owners driving requirement. $E_{max,j}$ denotes the charge rate in term of energy of individual EV. $w * E_{cap,j}$ means the recommended maximum SOC of the EV, where w is the parameter which express the

charging behavior of the battery of the EV is a linear process, $E_{cap,j}$ is the capacity of the battery of the EV.

With the above optimization problem, each EV agent can generate a unique energy schedule; the sum of the individual EV energy schedule in one FO will be denoted as $P_{k,i}^E$, and

$$P_{k,i}^E = \sum_{j=1}^{N_k^E} P_{ji}, k = 1, \dots, N_B, i = 1, \dots, N_T,$$

where N_B represents the number of the FOs, k denotes the index for the number of FOs, $k = 1, \dots, N_B$.

This is the key computation method that is used in this study for step 1 which is described in section 2.3. Then in step 2, 3, there is no issue needed to be clarified. In step 4, Distribution system operator pre-access and analyse the distribution network by running the load flow calculation in the simulink where a 10kV distribution network is modeled. The math behind step 5, 6, 7 will be explained in the following subsection.

3.2. Price based approach for distribution grid congestion management

To describe the price coordination method, we start with a proposed cost function which represents the cost of the power preference difference of a FO in each time slot, e.g.,

$$\mu_k = \zeta_k(\tilde{P}_{k,i}).$$

To facilitate the understanding, we assume

$$\mu_k = C_{k,i}(\tilde{P}_{k,i} - P_{k,i}^E)^2, \quad (2)$$

where $i, k, P_{k,i}^E$ keep the same with above notation, $\tilde{P}_{k,i}$ denotes the control variable, $C_{k,i}$ means the weighting factor which are associated with the power difference, the larger $C_{k,i}$ implies a smaller difference. The objective is to minimize the cost functions of all the FOs as well as respect to the constraint from the DSO:

$$\text{minimize} \quad \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i}(\tilde{P}_{k,i} - P_{k,i}^E)^2$$

subject to

$$\sum_{k=1}^{N_B} \tilde{P}_{k,i} \leq P_{Cap}(i), i = 1, \dots, N_T, \quad (3)$$

where $P_{Cap}(i)$ is the power capacity specifically for all the FOs, for example, it can be estimated by the DSO after deducting the conventional loads. This problem is a convex optimization problem and relevant research (Boyd and Vandenberghe, 2004; Boyd et al., 2007) show that by introducing Lagrange multipliers or shadow price $\Lambda(i) \in R^{N_T}$, problem (3) can be transferred into following partial Lagrangian problem:

$$L = \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i}(\tilde{P}_{k,i} - P_{k,i}^E)^2 + \sum_{i=1}^{N_T} \Lambda(i) \left(\sum_{k=1}^{N_B} \tilde{P}_{k,i} - P_{Cap}(i) \right) \quad (4)$$

The centralized optimization problem (3) is transferred into a decentralized one with associated shadow price $\Lambda(i)$ in each

time slot, with the purpose of emulating the market behavior. In the starting point, the shadow price is assumed to be zero, then the optimal solution for equation (4) are $P_{k,i}^E$. This explains the step 5 that FOs first directly submit their power schedule to the market operator and market operator will determine the shadow price. Since the market operator's interest is in alliance with the DSO, i.e., eliminating the grid congestion, as further explained in study (Hu et al., 2013) and (Boyd et al., 2003), the shadow price can be updated according to $\Lambda(i)^{\omega+1} = \Lambda(i)^\omega + \alpha_\omega \cdot (\sum_{k=1}^{N_B} P_{k,i}^*(\Lambda^*) - P_{Cap}(i))$ until the price converges, where $P_{k,i}^*(\Lambda^*)$ is the optimal solution of equation (4) with the given Λ^* , i.e., the newly $\Lambda(i)^{\omega+1}$, ω is the convergence steps needed, $\alpha_\omega \in R$ denotes the step size and can be chosen as $\alpha_\omega = \alpha$ which is a positive constant, independent of k ; with such choice, the convergence is guaranteed. This explains the step 6.

In step 7, FOs sends the shadow price to all the EV controller. Then EV controller restarts the step 1, the only difference is that a shadow price is added on the top of the predicted spot energy prices, and the modification compared to the study (Hu et al., 2013) lies on the response weighting factor γ to the shadow price. The EV owner can show their will by setting up this response weighting factors. For example, if γ is zero, it represents that the EV owner is fully insensitive to the shadow price and will keep the original power schedule; otherwise, a new power schedule will be generated and submitted to the FOs. By repeating the steps, the proposed solution can ensure the safety of the grid in the planning period.

4. Multi-agent model for control system demonstration

4.1. Multiagent system architecture

In order to demonstrate the operation of the control systems, a multi-agent system is utilized and developed in this study. Fig. 3 depicts the MAS system architecture, in which, all the agents are built in JACK which is an agent-oriented development environment built on top of and fully integrated with the Java programming language (Howden et al., 2001). JACK offers the environment and facilities message sending/receiving. Matlab based functions enables a declarative implementation of the decision module. Simulink is used to model the distribution grid and functioned for power flow calculation. The java application programming interface `matlabcontrol`² is used for JACK to interact with Matlab.

4.2. Introduction on the features of JACK

The agents used in the JACK are modeled according to the theoretical Belief Desire Intention (BDI) model of artificial intelligence (Wooldridge, 2008). Within the environment, a JACK agent is a software component that can exhibit reasoning behaviour under both pro-active (goal directed) and reactive (event driven) stimuli. As key components of JACK, the JACK agent language introduces five main class-level constructs:

- *Agent*: which models the main reasoning entities in JACK.

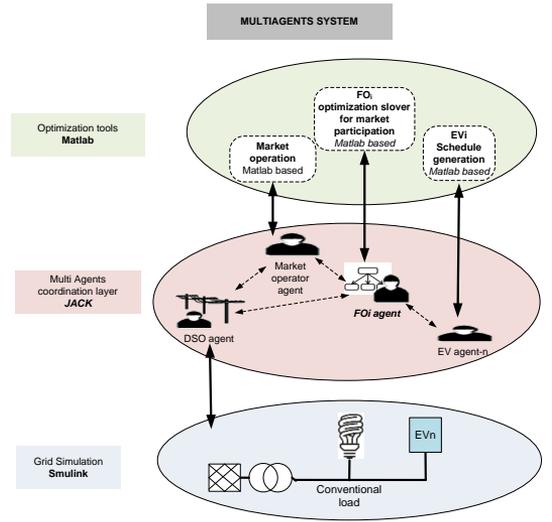


Figure 3: A MultiAgent system architecture.

- *Event*: which models occurrences and messages that these agents must be able to respond to.
- *Plan*: which models procedural descriptions of what an agent does to handle a given event. An agent's plans are analogous to functions.
- *Capability*: which aggregates functional components (events, plans, beliefsets and other capabilities) for agents to make use of.
- *Beliefset*: which models an agent's knowledge about the world.

In this study, we mainly use the three class levels: the agent class, the event class, and the plan class.

4.3. Use case and the MAS implementation

4.3.1. Agent class and its instantiation

Considering the features of JACK and the requirements of our desired systems, we use agent class in the design views which make the instantiation of an agent class flexible. Besides, each agent has several plans which are used to handle the events.

EV agent: An EV agent class is responsible for generating the charging schedule of individual EVs. They communicate with the subscribed FOs.

FO agent: A FO agent class is responsible for aggregating the charging schedule of their contracted EV agents and modifying the power schedule when negotiating with the market operator agent. In short, the FO agent communicates with EV agents, the DSO agent and the market operator agent.

DSO agent: A DSO agent is responsible for the grid safety by performing load flow calculation after obtaining the power

²<https://code.google.com/p/matlabcontrol/>

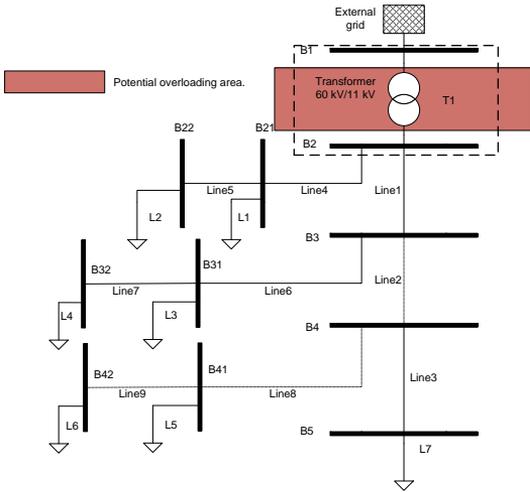


Figure 5: A 10kV distribution network.

schedule to the market operator agent by the some event *FOPowerSchedule*. If the price is converged, the market operator agent will send the final shadow price to the FO agent by the event *FinalShadowPrice*. The event will be handled by the FO agent with the plan *PriceCenterToEV*.

Plan *PriceCenterToEV*: In the plan, the FO agent does not sends the shadow price to the EV agent directly, because the calculation center is place on the FO agent level. Instead, it sends a normal message which stimulate the event *SelfPostInformation* again.

Note that when the price is converged, a complete sequence of the operation needed for grid congestion has been went through. However, the newly acceptable power schedule of the FOs might deviate the original plan. Therefore, we leave the chance to the FOs and the EV owners to make a new schedule based on the information of the first round. This explain the fact of sending the final shadow price to the FO agent by using the event *FinalShadowPrice*. In order to run the complete sequence again, the EV agents need a signal to stimulate the corresponding plans and this is achieved by the event *SelfPostInformation* sent out by the market operator agent using the plan *PriceCenterToEV*.

5. Simulation and demonstration results

5.1. Case study specification

A 10kV radial network is considered in this case study, the one-line diagram/topology of the network is shown in Fig. 5. The network is modified from Østergaard and Nielsen (2008); Han (2012), which can represent the typical features of a Danish distribution systems. The network consists of two voltage

level, 11 buses, 9 distribution lines, 7 load buses and the network is modeled in the Simulink. 1400 households is connected in this distribution systems, and 20% of the households is assumed to have EVs. Considering the similarities of the driving patterns of the EV users and simulation requirements of the multiagent systems, we divide the 280 EVs into 14 groups which is represented by 14 EV agents. Three FOs is assumed to provide services to these 14 EV agents. FO1 is responsible for EV agents EV1 to EV5. EV6 to EV9 is assigned to FO2. The rest of the EV agents subscribe to FO3. If all the EVs is connected to the grid at the same time, this will bring 644kW additional load to the network (Maximum individual EV charging rate is limited to 2.3 kW, this fits with the Danish case (10 A, 230 V connection)). In our case study, we set up the available power capacity for all the EVs is 600kW (available capacity of the primary transformer for EVs). The weighting factor rate $C_{1,i}$, $C_{2,i}$, $C_{3,i}$ is set to 0.5, 0.1, and 0.2. The value of α_ω is chosen as 0.1 in this case.

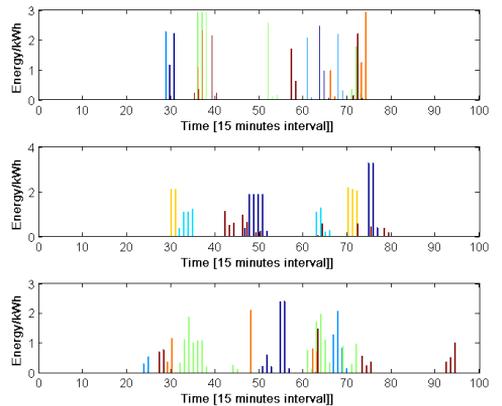


Figure 6: EV energy driving requirement per EV agent per FO.

For the EV charging schedule, the information of hourly electricity spot price of the Nordic power market ⁴ is assumed to be perfectly known by the EVs, and the price data is identical with previous study (Hu et al., 2013). The artificial driving data of the 14 EV agents have been generated based on the 2003 AKTA Survey [31], in which 360 cars in Copenhagen were tracked using GPS from 14 to 100 days. Each data file includes starting and finishing time, and the corresponding duration and distance. The original data is transferred into 15 minutes interval driving energy requirements based on the assumption of 11 kWh/100 km. The 15 minutes interval is changeable rather than absolute. The energy driving requirement of EV1 to EV14 is illustrated in Fig. 6. It is seen from Fig. 6 that most EVs have a regular pattern, i.e., they leave home in the morning time and come back in the evening time, while some EVs have higher energy driving requirement, such as EV agent EV13 which is

⁴<http://www.nordpoolspot.com/>

shown by the green curve of the bottom figure. For other parameters:

- Battery capacity of all the EV agents are set to 20 kWh.
- Initial SOC of all the EV agents are set to 0.2 of the battery capacity.
- Minimum SOC of all the EV agents are set to 0.2 of the battery capacity.
- Maximum SOC of all the EV agents are set to 0.85 of the battery capacity, the minimum and maximum SOC set up is to ensure that the EV charging process is linear.
- EV agents's responding weighting factor to the shadow price is assumed to be (0.01, 0.01, 0.01, 0, 0, 0.01, 0.01, 0, 0, 0.01, 0.01, 0.01, 0, 0), correspondingly.

5.2. Simulation results in MATLAB

In this simulation part, we compared the result of two cases where the DSO both use the price-oriented market protocols to interact with the FOs, however, the coordination methods between the FOs and the EVs are different. In the first case, we assume that three FOs centrally schedule and control the EV charging which is the scenario in work (Hu et al., 2013), while in the second case, it is assumed that three FOs only aggregate the charging schedules which are made by the EV controllers, this is the scenario in this study. As illustrated in Fig. 7, the congestion problems are solved after 5 steps in the first case while only 2 steps in the second case. The difference is because that the EVs in the first case are always responding the shadow price and trying to avoid the charging on the higher price period, as a result, the EVs will be scheduled to charge at other lower price period where congestion might happens as well. While in the second case, only some EVs are assumed to responds to the shadow price which means that only part of the charging plan is rescheduled to other lower price period and thereby reduce the possibility of causing a new congestion period. Note that in the beginning, the shadow price is zero, so the blue curves in the left part of Fig. 7 represent the spot electricity price. For the rest of the price curves, the spikes represents the shadow prices.

5.3. Demonstration result of the MAS

When setting up the demonstration of the MultiAgent system, the Simulink part is not included in this case study because the capacity limit is only considered for the transformer. Considering the two assumptions: 1) there is no power losses in the distribution network or we do not consider it. 2) the overhead line and underground cable are capable of handling the increasing loads, the power information below the transformer can be simply obtained by summing up the power schedule of the FOs instead of fetching it from the Simulink. For the rest of the system, it goes the same as we presented in Fig. 4. In JACK, there are a number of tools available to assist a detailed trace of the system execution which range from graphical tracing tools to logging tools. In this study, we run the program with the interaction diagram. As we have one DSO agent, one market

operator agent, three FO agents, and fourteen EVs agents, the interaction diagram which shows the communication message among them is quite large. It is not wise to show the whole interaction diagram in this paper, instead, we only show part of the interaction diagram where the message sequence happens between the DSO agent, the market operator agent named CMO, the FO agent FO1, and one EV agent EV1, this is shown in Fig. 8. The sequence diagram starts from agent EV1 (holds for other 13 EV agents) with a request of schedule calculation. Then the schedule information is aggregated by the FO agent and is sent to the DSO agent. The rectangular box marked with iteration represents the interactions between the market operator agent and the FO1 agent. It well emulates the negotiation behavior inside a capacity market. When the shadow price is converged, the shadow price is sent to the EV agent. With the new schedule, it is confirmed by the DSO agent that there will be no congestion for the grid in the planning phase, which means the programming stops.

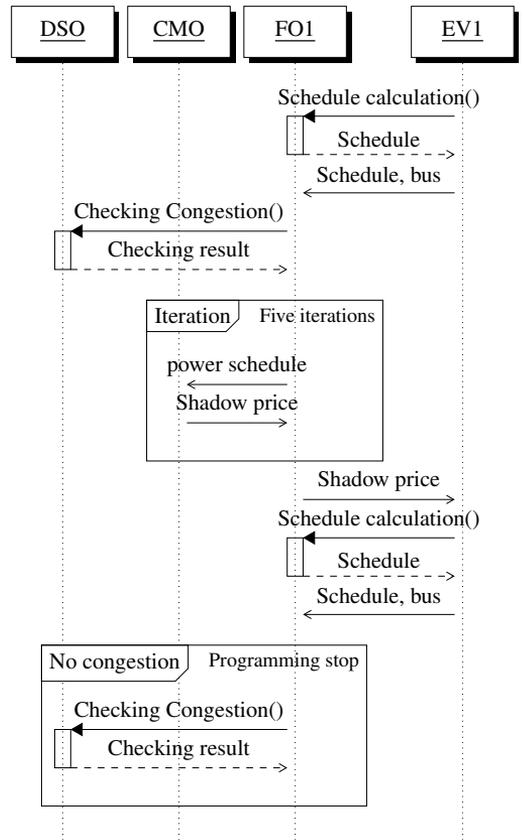
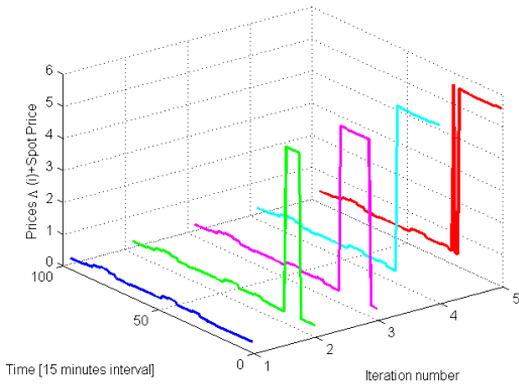
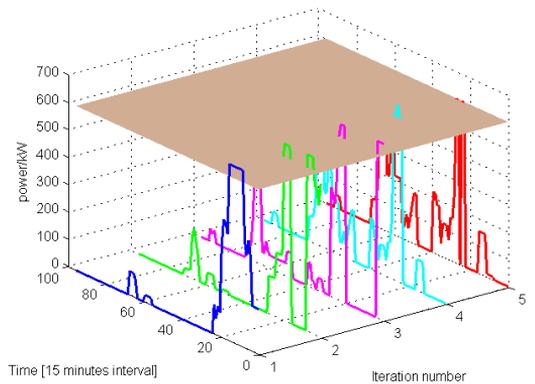


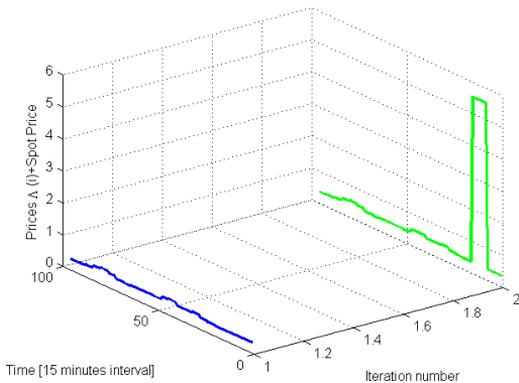
Figure 8: Sequence diagram between the chosen agents.



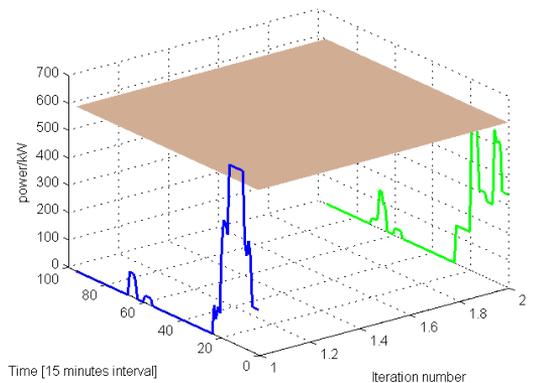
(a) The sum of the spot price and shadow price in each iteration step.



(b) The comparisons of FO's power schedule in each step with the power capacity.



(c) The sum of the spot price and shadow price in each iteration step.



(d) The comparisons of FO's power schedule in each step with the power capacity.

Figure 7: **Top:** Case study for centralized control between FOs and EVs. **Bottom:** Case study for decentralized control between FOs and EVs.

6. Discussion and conclusion

A multi-agent system is developed to demonstrate the distributed implementation of the grid congestion management scheme of distribution network with a large scale of EVs. It is learned from the experience that the distribution grid congestion can be eliminated according to economical principles, and a MAS based distributed implementation is of higher advantage. In this study, we develop and utilize an integrated environment consisting of JACK agent software and Matlab to analyze the cyberphysical aspects of the environment. This is because JACK is good for demonstrating the coordination schemes among the actors, and Matlab is good for technical computation of optimization problem. For a general case, various simulation platform can be utilized in a distribution grid congestion demonstration. For example, besides JACK, JADE is also widely used for multiagent simulation. We choose JACK because of its capability and support for the explicit modelling

of the typical MAS entities such as agent, plan, event and capabilities. Moreover, in JCK it is easier to design and analysis interactions and dependencies among such entities. In term of solving an optimization problem, GAMS also has good performance, however, Matlab is more widely used in the academically field. Last but not least, grid modeling tool is also an important part, the currently existing grid modeling tools include Simulink, MatPower, PowerFactory, ARISTO, NEPLAN etc. The scope of these listings is not to give a comparison about the various platforms, instead, we want to emphasize that the relevant tools can be integrated with the MAS settings.

Besides EVs, some other new loads such as heat pumps and the increasing electrification of the loads in the home will also bring challenges to the distribution grid. We believe that this multiagent framework can be used to address the similar challenges. Since the FOs (You, 2010) (Alternative names for an FO are used such as virtual power plant, aggregator) is also widely

proposed for aggregating other distributed energy resources. As expected, the FOs will represent the DERs and interact with the market operator and the DSO similarly with the one in this study.

Acknowledgment

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A.10 HV/MV power transformer capacity negotiation by fleet operators using multi-agents

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HV/MV Power Transformer Capacity Negotiation by Fleet Operators using Multi-agents

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Abstract. The integration of electric vehicles in future power systems will change their normal operations. The system operators will need to manage this new energy resource, considering the charge necessities as well as the discharge energy opportunities. Congestion situations can occur in some equipment's (lines and power transformers), mainly in peak periods. This paper proposes a hierarchical management structure considering the distribution system operator and a new entity called electric vehicles fleet operator. To simulate this collaborative (all players contribute to the operation system stability) but also competitive environment (each player will try to increase its profits or reduce its costs), a multi-agent platform was developed to demonstrate the interactions between the entities.

Keywords: Congestion Management, Electric Vehicles, Fleet Operators, Multi-agent Systems, Smart Grids

1 Introduction

Several policies were issued in recent years to improve the energy consumption efficiency, to change the energy mix and to reduce the greenhouse gas emissions. The incentives provided to distribution generation (DG) have been a success and in several countries, DG represents more than 20% in the electricity generation mix. The wind generators and solar photovoltaic panels are the technologies with higher growing. However, technologies such a micro-hydro generation or combined heat and power (CHP) represent important energy resources in several countries.

Despite the high penetration of DG technologies the governments in European countries defined ambitious goals for a near future. According the European energy roadmap 2050 [1] “*The EU is committed to reducing greenhouse gas emissions to 80-95% below 1990 levels by 2050 in the context of necessary reductions by developed countries as a group*”. In some countries, the goals are even more challenging. For example in Denmark, in 2020 the Danish government intends a reduction of 12% of energy consumption (in comparison with consumption in 2006) and also supplies 50% of the electricity consumption using wind generation [2]. In 2035 the Danish government intends to have all the power systems based on renewable resources and

in 2050 intends to have all the economy, including the power systems, the heating systems and also the transportation, based in renewable resources [3].

To achieve these objectives it is necessary more investment in DG but also in infrastructures (transmission and distribution networks) and in new management methodologies in order to assure the reliability in power systems operation. The use of storage units like batteries, pumped-hydro plants, compressed air energy storage or other technology is crucial for the future power systems based in renewable and intermittent resources.

In another point of view, to guarantee the greenhouse gas (GHG) emissions reduction it is necessary the decarbonisation of all activities, besides the power industries. The power industries were responsible for around 30% of GHG in EU-27 in 2011. The second sector with more GHG emissions in 2011 were the transports with a share of 20.3% [4]. To assure the GHG emissions reduction in transports and also in heating/cooling it is necessary the use of electricity in these sectors. The use of electric vehicles will be essential to assure the GHG emission reduction goals. In the end of 2012 had been sold more than 180 000 electric vehicles (EVs) in worldwide and are expected a total of 20 million on the road in 2020 [5].

The integration of these vehicles in the electric system will increase significantly the global power demand [1]. In this sense it is necessary develop new energy resources management strategies mainly in distribution level avoiding congestions in the network. EVs can be managed as a distributed energy resources providing a flexible storage system in low voltage distribution network [6]. EVs can be used as reserve providing different kind of ancillary services helping the system operators maintaining the system stability [7]. EVs are very flexible being potentially capable of enhancing the efficiency of other DERs. However, uncontrolled charging of EV can create new load peaks during the day, increasing power losses, the voltage deviations and the network congestion [8].

EV fleet operator (FO) is a new entity aiming to capture the business opportunities by providing the multiple services of EVs. EV FO could be independent or integrated in an existing business function of the energy supplier. EV FO intends to guarantee driving needs of the EV owners, coordinate and support the valuable services and operation constraints of EV and power system operator, maximize the renewable energy use, implement centralized control/marketing method to maximize business values, optimize the EVs charging and discharging processes [9].

In the present paper a multi-agent platform implemented to simulate the interactions between the EV FOs and the distribution system operator (DSO) and between the EV FOs and the EVs owners is presented. The main goal is the negotiation between the agents in order to avoid the congestion of the distribution network lines and mainly the HV/MV power transformer. Each EV FO has the capability to manage the EVs charge and discharge considering the energy prices and the EVs requirements (schedule trips, batteries technical limits, etc). The problem considers the network technical constraints namely the bus voltage magnitude and the lines thermal limits.

This paper is organized as follows: after this introductory section, section 2 presents a description about the fleet operators functioning, section 3 presents the congestion negotiation method, section 4 describes the implemented multi-agents plat-

form and the negotiation mechanism. The main conclusions of the paper are provided in section 5.

2 Fleet Operators

Fleet Operators (FO) can have different definitions according the context. In this specific case the FO can be described as the entities responsible for the electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEV) charge and discharge coordination [10]. The use of electric vehicles with gridable capability, normally called vehicle to grid (V2G) has been discussed in several papers [6], [11], [12] considering different management methodologies. The main conclusion of the EVs integration in distribution network studies and analysis is that the electric vehicles charge and discharge should be coordinated in order to avoid critical situations mainly during the peak periods. In fact the peak consumption can increase significantly if the all EVs charge at the same time. On the other hand, EVs can provide some interesting support to the distribution network operation functioning as small batteries capable to discharge energy to the network when the system operator has need.

Aggregators like virtual power plants or fleet operators will be crucial in a near future in order to coordinate the EVs charge and discharge process. The main goal is try to schedule the EVs charge during the off-peak periods and, when required, discharge energy in order to support the system operator in the distribution network management. Virtual Power Plants are players with the capability to manage several distributed energy resources technologies like distributed generation units, demand response programs, storage systems and electric vehicles [13], [14]. FOs is more focus in the EVs coordination considering the constraints imposed by the DSO, taking into account the network limitations and also the market opportunities in order to take advantages in the energy negotiation. In some situations FOs can also manage the loads consumption. In Fig. 1, the proposed architecture considering two FOs is presented.

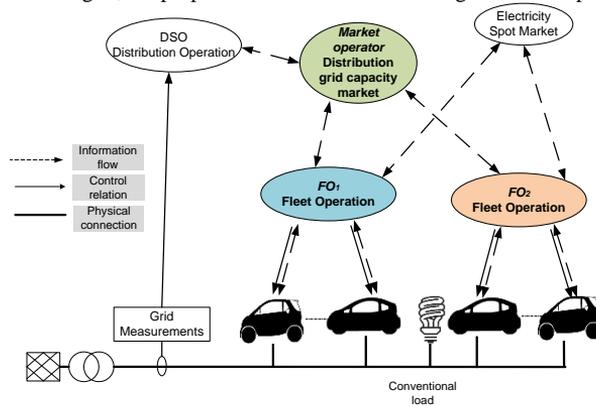


Fig. 1. A schematic of a low voltage active distribution system [9]

Fig. 1 presents a schematic of a low voltage distribution system, considering the connection of electric vehicles and the consumers. In this distribution system, it is assumed that the consumers own controllable devices, i.e., EVs, besides some conventional loads, such as light or TV. These EVs are divided into two groups as illustrated in Fig. 1. One group is controlled by fleet operator-1 (FO₁), another group is controlled by fleet operator-2 (FO₂). In this hierarchical distribution system, both FOs can schedule and control their customer's electricity consumption directly. While on the FO level, the coordination between FOs and DSO is made through the distribution grid capacity market. The capacity market is managed by the DSO allowing the use of distribution network in a competitive environment mainly in the peak periods. FOs can also negotiate energy in electricity markets and in bilateral negotiations with other agents [9].

The coordination between DSO and FOs is crucial to manage the distribution network use avoiding congestion situations [15], [16]. The congestion situations can occur in the lines but also in the power transformer. In the proposed methodology both type of congestions are considered. An AC Power flow is included in the FOs scheduling in order to avoid the congestion in the distribution network. However the use of power transformer should be managed by the DSO using a negotiation mechanism in order to allocate the power transformer to different FOs.

Each FO will do its EVs charge/discharge scheduling taking into account the network constraints. The scheduling is implemented as a mixed-integer non-linear problem (MINLP) trying to minimize the costs (1). The energy cost depends of the external suppliers as well as by the HV/MV power transformer capacity use. Each FO can use the energy stored in the EVs batteries avoiding congestion problems. The power losses in the distribution network are also considered in the problem. Expression (1) represents the implemented objective function.

$$\min Z = \sum_{t=1}^T \left(\left(\sum_{V2G=1}^{N_{V2G}} (P_{Ch(EV)} - P_{Dch(EV,t)}) + \sum_{l=1}^{N_l} (P_{Load(l,t)}) \right) \times c_{Cong(t)} + \left(\sum_{V2G=1}^{N_{V2G}} (P_{Dch(EV,t)} \times c_{Dch(EV,t)}) + \sum_{l=1}^{N_l} (P_{NSD(l,t)} \times c_{NSD(l,t)}) \right) \right) \quad (1)$$

In expression (1), the variables $P_{Ch(EV,t)}$ and $P_{Dch(EV,t)}$ represent the charge and discharge power of electric vehicles and the parameter $c_{Dch(EV,t)}$ the energy discharge cost. The loads are characterized by the consumption forecast $P_{Load(l,t)}$ and by the non-supplied demand $P_{NSD(l,t)}$. This parameter will be important to avoid the congestion situations in extreme situations, considering the cost $c_{NSD(l,t)}$. $c_{NSD(l,t)}$ can represent the cost with a demand response event or a penalization to load curtailment without any coordination or contract. The parame-

ter $C_{Cong(t)}$ represents the HV/MV power transformer congestion cost. This parameter is different in each negotiation iteration. In the first iteration $C_{Cong(t)}$ is zero, representing the situation without congestion.

The problem constraints consider the first Kirchhoff law relating to the active (2) and reactive (3) power balance considering that the energy is supplied by external suppliers SP and the distribution network technical limits regarding the lines thermal limits (4) and the bus voltage magnitude limits (5). The implemented AC power flow model is based in [17]. In expressions (2) to (5), the parameters i and j represent the bus i and j . Additionally, the problem considers the maximum power limit imposed by DSO regarding the HV/MV power transformer capacity use. The EVs constraints relating to the batteries energy capacity limits (6), the batteries internal energy balance (7) and the charge (8) and discharge (9) rates are also considered [18].

- Active Power Balance

$$\sum_{SP=1}^{N_{SP}^i} P_{SP(SP,t)}^i + \sum_{V=1}^{N_V^i} \left(P_{Dch(EV,t)}^i - P_{Ch(EV,t)}^i \right) - \sum_{L=1}^{N_L^i} \left(P_{Load(L,t)}^i - P_{NSD(L,t)}^i \right) =$$

$$G_{ij} V_{i(t)}^2 + V_{i(t)} \sum_{j \in L} V_{j(t)} \left(G_{ij} \cos \theta_{ij(t)} + B_{ij} \sin \theta_{ij(t)} \right)$$

$$\forall t \in \{1, \dots, T\}; \forall i \in \{1, \dots, N_B\}; \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)}$$
(2)

- Reactive Power Balance

$$\sum_{SP=1}^{N_{SP}^i} Q_{SP(SP,t)}^i - \sum_{L=1}^{N_L^i} \left(Q_{Load(L,t)}^i - Q_{NSD(L,t)}^i \right) =$$

$$V_{i(t)} \sum_{j \in L} V_{j(t)} \left(G_{ij} \sin \theta_{ij(t)} - B_{ij} \cos \theta_{ij(t)} \right) - B_{ii} V_{i(t)}^2$$

$$\forall t \in \{1, \dots, T\}; \forall i \in \{1, \dots, N_B\}; \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)}$$
(3)

- Lines thermal limits

$$\left| \overline{U_{i(t)}} \times \left[\overline{y_{ij}} \times \left(\overline{U_{i(t)}} - \overline{U_{j(t)}} \right) + \overline{y_{sh_i}} \times \overline{U_{i(t)}} \right] \right|^n \leq S_{Lk}^{max}$$

$$\left| \overline{U_{j(t)}} \times \left[\overline{y_{ij}} \times \left(\overline{U_{j(t)}} - \overline{U_{i(t)}} \right) + \overline{y_{sh_j}} \times \overline{U_{j(t)}} \right] \right|^n \leq S_{Lk}^{max}$$

$$\forall t \in \{1, \dots, T\}; \forall i, j \in \{1, \dots, N_B\}; i \neq j; \forall k \in \{1, \dots, N_K\}$$
(4)

- Bus voltage magnitude limits

$$V_{Min}^i \leq V_{i(t)} \leq V_{Max}^i \quad ; \forall t \in \{1, \dots, T\}$$
(5)

- Energy stored limits in EVs batteries in each period t

$$E_{St_Min}(EV,t) \leq E_{Stored}(EV,t) \leq E_{St_Max}(EV,t) \quad (6)$$

- Energy balance in EVs batteries in each period t

$$E_{Stored}(EV,t) = E_{Stored}(EV,t-1) - E_{Trip}(EV,t) + \eta_{c(EV)} \times P_{Ch}(EV,t) - \frac{1}{\eta_{d(EV)}} \times P_{Dch}(EV,t) \quad (7)$$

- Charge and discharge rates in each period t

$$P_{Ch}(EV,t) \leq P_{Ch_Max}(EV,t) \quad (8)$$

$$P_{Dch}(EV,t) \leq P_{Dch_Max}(EV,t) \quad (9)$$

3 HV/MV Power Transformer use negotiation

The distribution networks have normally the capacity to accommodate all the connected loads considering the consumption evolution for next couple of years. However, a large penetration of EVs will bring some challenges to the distribution system operators or utilities. The challenges usually include peak power issue, grid congestion problem, power losses, voltage drop et al. Much research has been performed to study the intelligent EV load control and their effect on the grid, which can be dated back to the early 1980s [19]. In [19] the author argued that load management should be deployed to alleviate peak loading, which is measured in term of load factor improvement. Even low penetration levels of EVs can create new peak loads exceeding the natural peak if sufficient attention is not paid to distribute the charging load throughout the off-peak period [20]. A penetration level of 20% is found to be the upper limit which could be managed by distributing the charging load. Basically, those studies mainly investigated the impacts by adding the new EV loading profile to the already existing load profile and seeing the overall effect and then proposed the load shifting strategy.

Figure 2 presents a much advanced control strategy to prevent the grid congestions. In the first step, each fleet operator performs the EVs charge and discharge scheduling considering the inexistence of any congestion in HV/MV power transformer. However, a congestion situation inside the distribution network can be avoided due to the inclusion an AC power flow in the optimization problem constraints. Each FO sends the initial schedule to the distribution system operator in order to validate the initial proposals. If the limit of power transformer is not achieved, the DSO approves the proposals and each FO can communicate the decision to the electric vehicles owners.

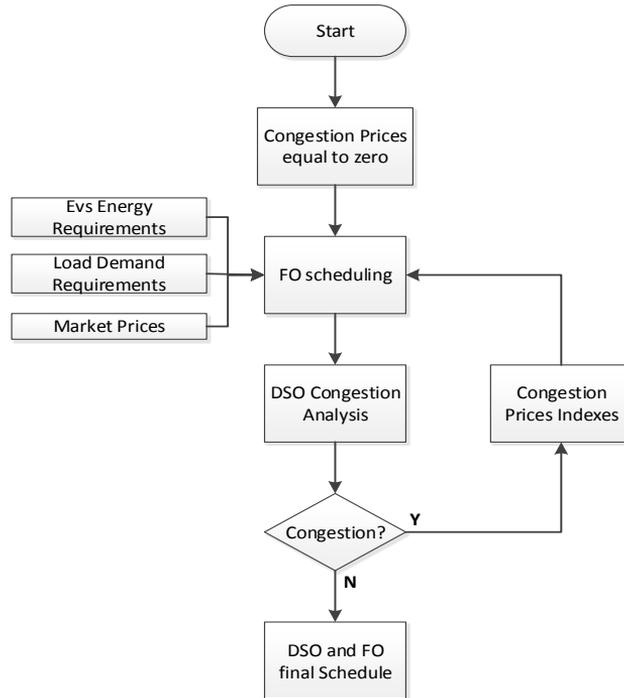


Fig. 2. Negotiation process

If the amount of required energy was higher than the power transformer capacity, the DSO will determine the congestion cost and send this information to the FO. Each FO will re-dispatch the EVs charge and discharge considering the new congestion price. The process finishes when the congestion ceases to exist.

4 Multi-agent Simulation Platform

A multi-agent system is used to implement the negotiation process. The platform is implemented using the JACK platform. JACK is an agent-oriented development environment built on top of Java programming language [21].

To simulate the derived problem, four different agents were developed namely:

- **EV agent:** An EV agent class is responsible for generating the charging schedule of individual EVs. They communicate with the subscribed FOs.
- **FO agent:** A FO agent class is responsible for EVs management and to the negotiation with the DSO. In short, the FO agent communicates with EV agents, the DSO agent and the market operator agent.

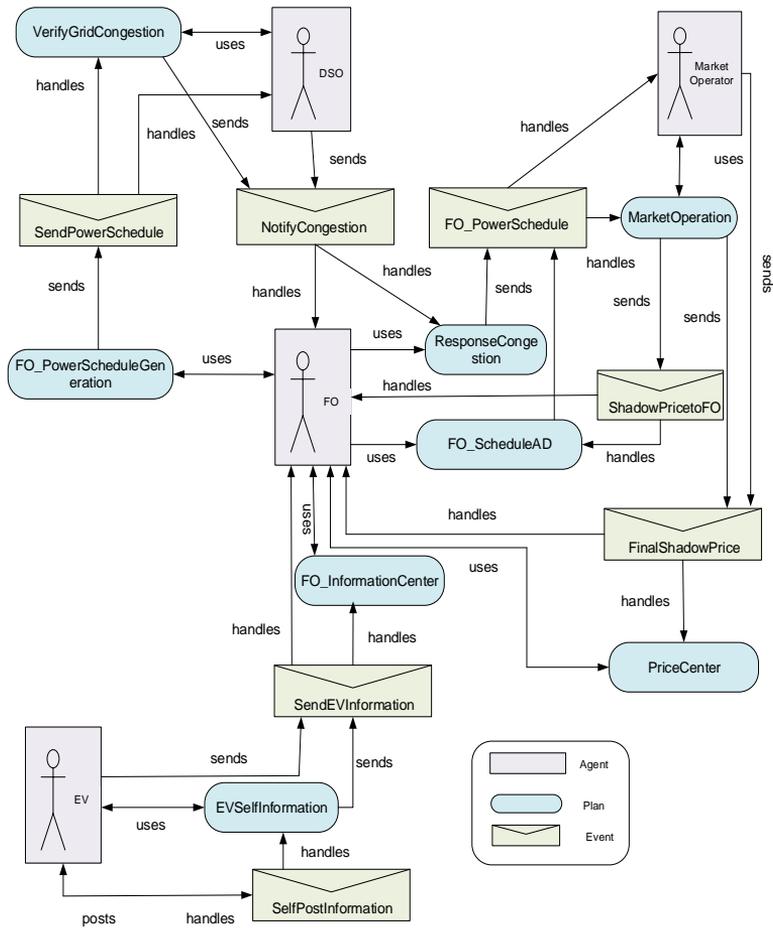


Fig. 3. Multi-Agent application in JACK

- **DSO agent:** A DSO agent is responsible for the grid safety by performing load flow calculation after obtaining the power schedules of FOs. The DSO agent communicates with the FOs agent and the market operator agent.
- **Market operator agent:** A market operator agent is responsible for making of the shadow price. The market operator agent communicates with the DSO agent and the FOs agent.

Fig. 3 shows the whole design diagram for the desired multi-agent systems in the JACK, which is built according to the proposed solutions in this study. The diagram is explained according to the sequence of the steps and is divided into three parts. Besides, the content inside each box of this diagram (mainly the content inside the plans of each agent) will be explained.

The interaction between agents can be explained as following:

- The interaction between the EV agent and the FO agent.
 - Event **SelfPostInformation**: Posted by the EV agent, the purpose is to trigger the plan *EVSelfInformation*.
 - Plan **EVSelfInformation**: The EV agent read the information including initial SOC, the driving requirement of the EVs in the scheduling period, and the bus information. After obtaining the personal information, the EV agent sends an event named *SendEVInformation* to the FO agent, and the event will be handled by the plan *FO_InformationCenter*.
 - Plan **FO_InformationCenter**: The EV information will be collected here and prepared for schedule generation.
 - Plan **FOPowerScheduleGeneration**: An Matlab based program will be called and be used to generate the charging power schedule. The power schedule will be sent to the DSO agent by using the event *ChargingSchedule*.

- The interaction between the FO agent and the DSO agent
 - Event **SendPowerSchedule**: Each FO agent sends the aggregated power schedule to the DSO agent by this event. The event will be handled by the DSO agent with the plan *VerifyGridCongestion*.
 - Plan **VerifyGridCongestion**: The DSO agent will call the grid model built in Matlab with the newly power schedule of the FOs and the conventional loads and do the power flow calculation. The DSO agent can fetch the value from the matlab and compare it with the capacity of the distribution grid, such as the transformers. Then the DSO agent will send the result to all the FO agents through the event named *NotifyCongestion*. The event will be handled by the plan *ReponseCongestion*.
 - Plan **ReponseCongestion**: All the FO agents get the result and check whether congestion exists. If it is congested, all the FO agents will resort to the market operator agent to negotiate the power capacity. Otherwise, the FO agents are allowed to bid the energy schedule into the energy spot market.

- The interaction between the FO agent and the Market operator agent
 - Event **FOPowerSchedule**: FO agent sends the power schedule to the market operator agent by this event and the event will be handled by the market operator agent with the plan *MarketOperation*.
 - Plan **MarketOperation**: In the plan, the market operator agent calls the matlab based price determination program and check whether the price is converged each iteration. If the price is not converged, the market opera-

tor agent will send the updated shadow price to the FO agent by the event *ShadowPriceToFO*. Accordingly, this event will be handled by the agent with the plan *FOScheduleAD*.

- Plan **FOScheduleAD**: In the plan, the FO agent will reschedule the power and resend the power schedule to the market operator agent by the some event *FOPowerSchedule*. If the price converged, the market operator agent will send the final shadow price to the FO agent by the event *FinalShadowPrice*. The event will be handled by the FO agent with the plan *PriceCenterToEV*.
- Plan **PriceCenterToEV**: In the plan, the FO agent uses the shadow price to recalculate the power schedule.

Note that when the price is converged, a complete sequence of the operation needed for grid congestion has been went through. However, the newly acceptable power schedule of the FOs may deviate from the original plan. Therefore, we leave the chance to the FOs and the EV owners to make a new schedule based on the information of the first round. This explains the fact of sending the final shadow price to the FO agent by using the event *FinalShadow-Price*.

5 Conclusions

The growing integration of electric vehicles in power systems introduces new challenges in the distribution networks. In many situations some congestion problems can occur in different points of distribution networks. The most critical ones will be the lines thermal limits and also in the HV/MV power transformers. In this paper a hierarchical management structure is presented including the distribution system operator (DSO) and the electric vehicles fleet operator (EV FO). The negotiation between EV FO and DSO is discussed considering a market base negotiation in congestion situations. The implemented negotiation architecture in multi-agent platform JACK is explained considering also the electricity market operator agent and the electric vehicles owners' agent.

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APPENDIX B

Supplementary background and methods

This section includes some details that facilitate the reading in the main contents of this thesis.

B.1 Battery modeling-Continuous

In a steady state battery equivalent circuit, by some deductions [8, 20, 28, 70], the battery current is obtained as:

$$I_2(soc, P_2) = \frac{U_{oc}(soc) - \sqrt{U_{oc}(soc)^2 - 4.R_{int}(soc).P_2}}{2R_{int}(soc)} \quad (B.1)$$

where P_2 is the terminal power. In order to study the optimization charging schedule for electric vehicle battery, two approaches are considered subsequently. One considers the electric vehicle battery as a pack [25,26,100], another considers the battery as aggregated cells and usually a battery cell is investigated firstly [20, 28]. If the dynamics of the state of charge of the battery is calculated by adding kWh into the available capacity, it usually starts with the calculation of

internal power of the battery P_{int} which is obtained as:

$$P_{int}(soc, P_2) = \begin{cases} -\eta \cdot I_2(soc, P_2) U_{oc}(soc) & P_2 \geq 0 \\ -\frac{1}{\eta} \cdot I_2(soc, P_2) U_{oc}(soc) & P_2 < 0 \end{cases} \quad (B.2)$$

The efficiency is a function of the battery current

$$\eta = 1 + \frac{\partial \eta}{\partial c} \cdot \frac{|I_2(soc, P_2)|}{Q_{max}} \quad (B.3)$$

where $\frac{\partial \eta}{\partial c}$ is a constant reflecting the decrease in efficiency with increasing current, Q_{max} is the battery capacity. Usually, linear and nonlinear approximation are used to characterize the relation between the internal power P_{int} and external power P_2 . Using linear approximation, the internal power is assumed to be equal to the external power. In this case all internal losses in the battery are neglected. Using nonlinear approximation, such the study in [25] used a second-order Taylor series expansion to derive the relation. The studies [8, 25] have shown that the difference between the two charging schedules is minor and indicates that the linear approximation is sufficient and the benefit of using a nonlinear approximation does not justify the increase in computation time.

And if the dynamic of the state of charge of the battery is characterize by the calculation of the dynamics of the electric charge, it models the battery charging with a first-order system which is described as:

$$x_{k+1} = x_k + \Delta t \cdot \frac{I_2(x_k, k)}{Q_{max}} \quad (B.4)$$

where x_k is an actual state of charge of the cell at the step k , Q_{max} is the battery capacity, I_2 can be calculated the same way as in the equation B.3.

Note if the battery cell is modeled, the parameter of the variables will be scaled down, e.g., divided by the numbers of the cells in a battery pack. For example, in order to calculate the external power P_2 in the cell based model, it can be obtained by the following equation:

$$P_2 = \frac{P_{BT}}{n_s} \quad (B.5)$$

where n_s is the number of the cells, and

$$P_{BT}(k) = \begin{cases} -\eta_k \cdot u_k \cdot P_{max} & k \in K_{plug} \\ P_{dr} & k \in K_{driv} \end{cases} \quad (B.6)$$

where η_k denotes the efficiency parameter, P_{max} means the maximum charge power when the EV is connected to the grid, u_k is the control variable. Now, the problem is formulated to find the optimal control strategy $u^* = \{u_0^*, u_1^*, \dots, u_{N-1}^*\}$, the details are presented in the following section 3.2.2.2 or in the study [20, 28].

B.2 Price control for regulating electric vehicles' charging behavior

In this case study, a 10kV distribution network [101] is considered where the number of electric vehicles is assumed to be 630 consisting 20% of the customer numbers. Normally, the distribution of the parameters $\alpha, \beta, \gamma, \delta$ reflects the user's preferences, which can be obtained through survey or data feedback. In our case, the total considered time slots are 14, i.e., the scheduling period is from 16 : 00 in the afternoon to 6 : 00 in the next day's morning. The parameters distribution $\alpha, \beta, \gamma, \delta$ is assumed independent, and the probability function of α is set as $f_\alpha(t) = \{5/39, 6/39, 7/39, 2/39, 3/39, 2/39, 1/39, 1/39, 1/39, 1/39, 1/39, 2/39, 3/39, 4/39\}$. β, γ, δ are assumed to be uniformly distributed within $[1, 20]$, $[1, 14]$ and $[0.01, 3]$ respectively. To better reflect the reality, among 630 EVs, each 20% are supposed to be charged from 4 kWh, 6 kWh, 8 kWh, 10 kWh and 12 kWh to 24 kWh respectively. So the total of initial load requested from users in the scheduling period will be $X_0 = 630 * 20\% * [(24 - 4) + (24 - 6) + (24 - 8) + (24 - 10) + (24 - 12)]$ kWh = 10.08 MWh. The initial requested load will be calculated by $L_t = X_0 * f_\alpha(t)$. The price information $p_0 = [0.3876, 0.3951, 0.4734, 0.5338, 0.4943, 0.4101, 0.3774, 0.3642, 0.3563, 0.3514, 0.3502, 0.3498, 0.3514, 0.3627]$ DKK/kWh used in A.6 is used in this case.

From the assumed value of $f_\alpha(t)$, the probability reaches max during the time slot 18 : 00–19 : 00, so we increase the price in this time slot to 0.9468 or 1.4202, i.e., two or three times of the original price 0.4734. The results are shown in Fig. B.1 (b) and (c), respectively. For comparison, the dynamic price which is a function of the initial load L_t is also studied (Fig. B.1(d)). The relationship is set as follows:

$$p(t) = 0.28 * L_t + 0.2 \quad (\text{B.7})$$

Following this equation, the average price will be 0.4 DKK/kWh which is consistent with the electricity market price.

As can be seen from Fig. B.1 (a)-(c), when the price increases at $t = 3$ (18 : 00 – 19 : 00), the loads will be shifted mainly to the time slot $t = 4$ and flatten the demand curve. Fig. B.1 shows that the peak of the load curve will be suppressed due to the high electricity prices resulted from equation B.2.

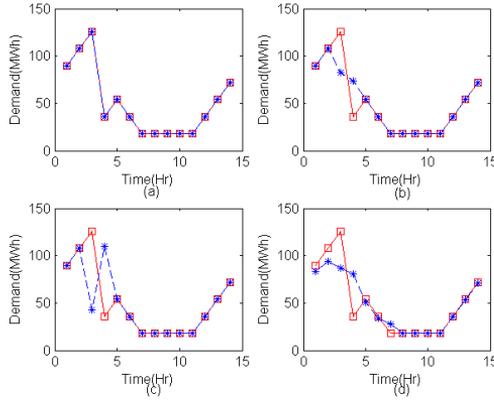


Figure B.1: Load profiles with price control, red curve means requested load and blue curve represents load with price control. (a) $p(t) = p_0$. (b) $p(t) = p_0, \forall t \neq 3, p(3) = 0.9468$. (c) $p(t) = p_0, \forall t \neq 3, p(3) = 1.4202$. (d) $p(t) = F(L_t)$

B.3 Congestion management principles in transmission systems

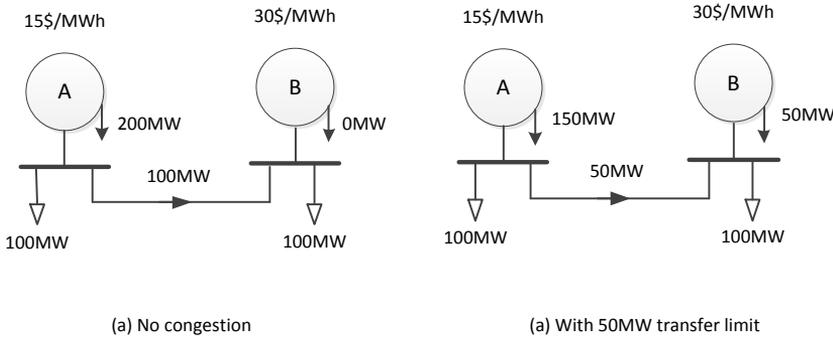


Figure B.2: Two zone system.

In transmission systems, congestion management is to control the system so that transfer limits (including thermal limits, voltage limits, and stability limits) are observed and not violated. In the deregulated power system, the challenge of congestion management for the system operator is to create a set of rules that must be robust and should be fair as well. Robust is required because there will

be many aggressive entities seeking to exploit congestion to create market power and increased profits for themselves at the expense of market inefficiency. As illustrated in Fig. B.2, if there is no transfer limits between zones, all 200 MW of the load will be bought from generator A at \$15/MWh, resulting a cost of \$3000/h. If there is a 50MW transfer limit, then 150MWh will be bought from A at \$15/MWh and the remaining 50MWh must be bought from generator B at \$30/MWh, a total cost of \$3750/h. Congestion has created a market inefficiency of 25% of the optimal costs, even without strategic behavior by the generators. Congestion has created unlimited market power for generator B if the demand at zone B is zero price elasticity. Fairness is required because the transmission line will probably used by many participants, as shown in Fig. B.3. If congestion happens, the tariff generated should be clear to all participants why the tariff has occurred. With a market approach, the form of congestion management is dependent on the energy market (electricity spot market for congestion prevention, regulating power market for buyback mechanisms).

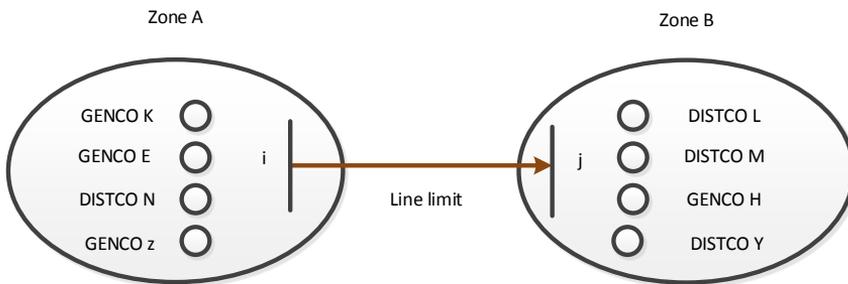


Figure B.3: Transmission congestion illustration: the transmission line between zone A and zone B will be congested due to the capacity limit.

Three forms of congestion managements have been developed for the deregulated power systems [102]. One form is a centralized optimization based approach, either explicitly with some form of optimal power flow program, or implicitly, depending on system operators to control congestion, found in various implementations in the United Kingdom, part of the United States, and in Australia and New Zealand. The second form is based on the use of price signals derived from ex ante market resolution to deter congestion before real time operation, used in the Nordpool market area. Inevitably some congestion may still arise and must be corrected in real time by purchasing of generation and consumption modifications from the system operator regulating markets, also known as buy-back. The third form seeks to control congestion by allowing and disallowing bilateral transmission, based on the effect of the transaction on the transmission system, found in part of United States. Strengths and weakness of the three

techniques are further discussed in the study [102]. The techniques discussed above can be divided into deterrent techniques, which attempt to schedule generation prior to operation in such a way as to avoid congestion, and corrective techniques, which control generation at the point of real time operation to prevent congestion.

Before thinking the application of the techniques. However, a question would naturally arise on the similarities and differences between transmission system and distribution network congestion as well as the solution to eliminate the congestions on both systems, here are our analysis:

- The complexity level is different.

Congestion occurs when the scheduled energy exceeds the available transmission capacity in either the day-ahead or the hour-ahead market. If congestion happens, the system operator will call for scheduling adjustment to eliminate the congestion according to the bids and offers received from producers and customers. In the transmission system level, this is possible due to the limited producers and customers. In practical, the system operator select the accepted bids and offers and set prices to clear the market. The decisions must maximize the economics welfare generated by the system while satisfying the security considerations. However, this is nearly impossible to achieve in the distribution network, since thousands of families together cause the congestions, it is quite complex and difficult to find a suitable economical principle which allocates the power capacity.

- The problem source and solution is different.

Fig. B.3 and B.4 illustrate an example of congestion happened in the distribution network and transmission lines. In the distribution system, the overloading happens in the transformer level, it is caused by the load below the transformer. Therefore, the solution is to decrease the peak load or shift the peak load. Note that distributed generation such as solar power is not considered. In the transmission system, the overloading usually happens on the transmission lines, as illustrated in the Fig. B.3, there is a congestion on the line from bus i to bus j . To eliminate the congestion, the GENCO and DISTCO in zone A and B can be divided into two groups. The first group represents the agents whose decremental adjustments could mitigate the congestion; the second group represents the agents whose incremental adjustment could mitigate the congestion. From this simple comparison, it seems that congestion management in the distribution level is unidirectional, e.g., reduce the load consumption under transformers

- The congestion effect/cost is different.

Congestion in the transmission system level can lead various marginal system price, which means the optimal resource can not utilized when the congestion exists. The congestion in the distribution network level usually effects the assets' life and because it seldom happens currently. Also because the grid is over capacity when building new lines and the typical approach is to plan the future capacity expansion when the capacity is fully used.

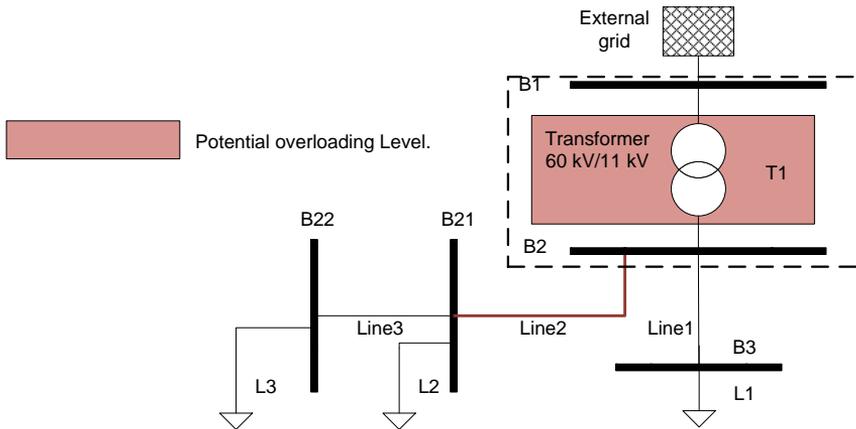


Figure B.4: Distribution congestion illustration: the transformer and the transmission line 2 will be challenged due to the increasing load below it.

B.4 Contract net protocols and auction approach

General equilibrium market mechanisms use global prices, and the price is usually coordinated by a centralized mediator. Contract net protocols [103], however, defines that individual nodes are not designated a priori as managers or contractors, these are only roles, and any node can take on either role dynamically during the course of problem solving. In his article [103], Smith defined that a manager is responsible for monitoring the execution of a task and processing the results of its execution. A contractor is responsible for the actual execution of the task. Although this is an effective way for reach an consensus when facing the conflicting resources, it is not suitable for the present problems from the system operator's perspective.

Auction can be designed as either single-sided auctions such as the case in the

regulation market or two sided auctions such as the case in the spot market. In the single-sided auction, offers are ranked in increasing order and accepted beginning with the least expensive and continuing until the demand is satisfied. The uniform price is then set equal to either the last accepted offer (LAO) or the first rejected offer (FRO). In two-sided auctions, offers and bids are ranked as above, and an equal quantity of each is accepted, beginning with the highest bids and lowest offers, until supply or demand is exhausted or the offer price exceeds the bid price. It is noted that the uniform price auction mechanism is usually combined with optimal power flow calculation [104], which mean either DSO/Market operator will implement a lot of calculations for distribution grid congestion management when using the uniform price auction mechanism.

B.5 Decomposition methods and subgradient method

This subsection provides a tutorial on the method of combining the subgradient method with dual decomposition techniques, as they are the mathematical techniques which support the development of the market based control. We firstly introduce the definition of subgradient. Subgradient, alternatively named subderivative, subdifferential generalizes the derivative to functions which are not differentiable. Let $f : I \rightarrow R$ be a real-valued convex function defined on an open interval of the real line. Such a function need not be differentiable at all points. For example, the absolute function $f(x) = |x|$ is nondifferentiable when $x = 0$. However, as seen in the figure B.5, for any x_0 in the domain of the function one can draw a line which goes through the point $(x_0, f(x_0))$ and which is everywhere either touching or below the graph of f . The slope of such a line is called a subderivative (because the line is under the graph of f) and that a subgradient of f at x_0 is any vector g that satisfied the inequality $f(x) - f(x_0) \geq g^T(x - x_0)$ for all x . When f is differentiable, the only possible choice for g^T is $\Delta f(x)$, and the subgradient method then reduces to the gradient method. The set of all subgradients at x_0 is called the subdifferential of f at x_0 , denoted $\partial f(x)$. So the condition that a subgradient of f at x_0 can be written $g^T \in \partial f(x)$

To introduce the subgradient method, we start with an unconstrained case, where the goal is to minimize $f : R^n \rightarrow R$, which is convex. The subgradient method uses the simple iteration

$$x^{(k+1)} = x^{(k)} - \alpha_k g^{(k)}. \quad (\text{B.8})$$

Where $x^{(k)}$ is the k th iterate, $g^{(k)}$ is any subgradient of f at $x^{(k)}$, and α_k is the k th step size. Thus, at each iteration of the subgradient method, we take a step

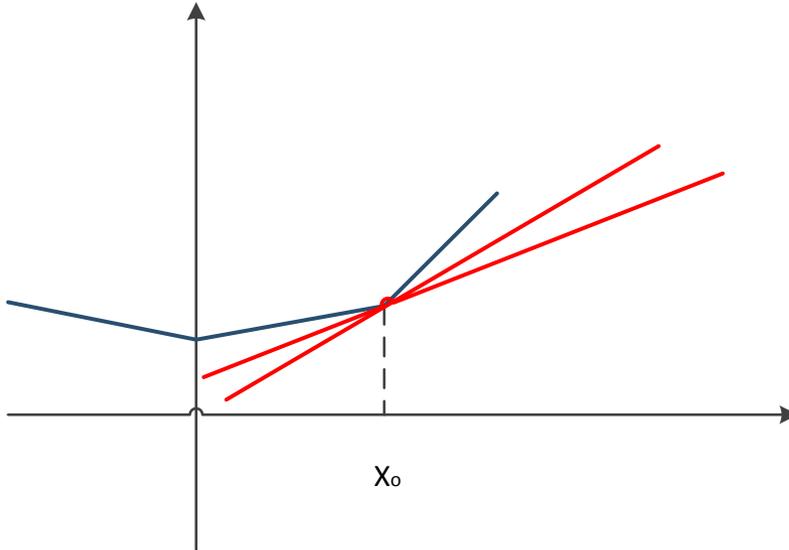


Figure B.5: A convex function (blue) and "subtangent lines" (red) at x_0 .

in the direction of a negative subgradient. Further discussions such as step size rules, convergence results are presented in [105]

As discussed in [105, 106], subgradient methods are often applied to large-scale problems with decomposition techniques. Such decomposition methods often allow a simple distributed method for a problem. The original primary motivation for decomposition methods was to solve very large problems that were beyond the reach of standard techniques, possibly using multiple processors. It is still a good reason to use decomposition method for some problems. But other reasons are emerging as equally (or more) important such as decomposition methods yield decentralized solution methods in many cases. Two decomposition methods are presented in [105, 106], i.e., primal decomposition and dual decomposition. We will briefly introduce the dual decomposition method since the dual variables (shadow prices or prices) are manipulated to solve the global problem. To introduce the dual decomposition method, we consider a simple example where the two subproblems are coupled via constraints that involve both sets of variables

$$\text{minimize } f_1(x_1) + f_2(x_2)$$

subject to

$$x_1 \in \zeta_1, x_2 \in \zeta_2, h_1(x_1) + h_2(x_2) \leq 0 \quad (\text{B.9})$$

where ζ_1 and ζ_2 are the feasible sets of the subproblems, presumably described by linear equalities and convex inequalities. The functions $h_1 : R^n \rightarrow R^p$ and $h_2 : R^n \rightarrow R^p$ have components that are convex. The subproblems are coupled via the p constraint that involve both x_1 and x_2 . By using dual decomposition, the problem B.9 is transformed into a partial Lagrangian problem,

$$\begin{aligned} L(x_1, x_2, \lambda) &= f_1(x_1) + f_2(x_2) + \lambda^T (h_1(x_1) + h_2(x_2)) \\ &= (f_1(x_1) + \lambda^T h_1(x_1)) + (f_2(x_2) + \lambda^T h_2(x_2)) \end{aligned}$$

which is separable, therefore, the problem can be minimized over x_1 and x_2 separately, given the dual variable λ , to find $g(\lambda) = g_1(\lambda) + g_2(\lambda)$. The $g_1(\lambda)$ is found by solving the subproblem

$$\text{minimize } f_1(x_1) + \lambda^T h_1(x_1)$$

subject to

$$x_1 \in \zeta_1 \quad (\text{B.10})$$

and the $g_2(\lambda)$ is found by solving the subproblem

$$\text{minimize } f_2(x_2) + \lambda^T h_2(x_2)$$

subject to

$$x_2 \in \zeta_2 \quad (\text{B.11})$$

To find a subgradient of g , the master problem objective is to get solution \bar{x}_1 and \bar{x}_2 , respectively. A subgradient of $-g$ is then $h_1(\bar{x}_1) + h_2(\bar{x}_2)$. It is proposed in [105, 106] that a simple algorithm based on subgradient method can be used to update λ .

Repeat

Solve the subproblems:

Solve (B.10) to find an optimal \bar{x}_1 .

Solve (B.11) to find an optimal \bar{x}_2 .

Update dual variables (prices) until the prices converge:

$$\lambda = (\lambda + \alpha_k (h_1(\bar{x}_1) + h_2(\bar{x}_2)))_+$$

B.6 Market based control-Negotiation types

It is discussed in [107, 108] that the negotiations can be characterized as either strident antagonist or cooperative antagonist. The former is characterized by completely distrustful and malevolent (towards one another) parties, as would be the case when authorities negotiate with kidnappers or airline hijackers. The latter is characterized by entirely self-interested and disputing parties but ones that recognize and abide by whatever rules exist. A third type of negotiation is called fully cooperative, where the parties have different needs, values, and opinions, but they share information, expect total honesty, perform no strategic posturing, and think of themselves as a cohesive entity with intention to arrive at the best decision for the entity, as would be the case for a happily married couple. We are interested here in the two different levels of cooperative negotiations, since they better typify the various types of power system decision problems. For example, a negotiation involving all smart appliances about the use of a certain amount of electricity at a smart home is a good example of fully cooperative negotiation, since the fundamental aim is to optimize the operation of the electricity at residential level. On a higher level, two commercial aggregators negotiating on a common transmission line could be a good example of cooperative antagonists.

B.7 Alternating direction method of multipliers (ADMM)

The alternating direction method of multipliers are used here to devise the price mechanism which can be used to solve the grid congestions. We firstly divide a distribution network into several sub-networks, each network is associated with inputs such as the local renewable energy, and the power transfer line and outputs such as the load, the power transfer line. We start the problem analysis by formulating it into an optimal power flow (OPF) based problem. Typically, the OPF can be solved centrally. However, in the distribution network, it might be infeasible considering the number of small units, the fluctuating generation and load profiles. Instead, we turn our solution to the distributed techniques, i.e., the ADMM solution [109]. The proposed method is illustrated by the following pseud code:

Step 1: DSO designs the sub-network systems and specifies an operator for each sub-network.

Step 2: Price coordination

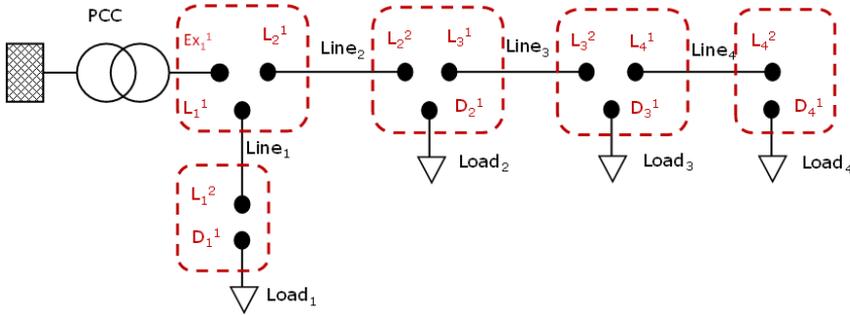


Figure B.6: A illustrative distribution network.

Parameters initialization.

Iterations:

(1) EV fleet operator calculates the power and phase schedules of EVs and passes it to the sub-network operator (e.g., a function of DSO).

(2) DSO line operator calculates the power and phase schedule of the transfer lines and passes it to the sub-network operator.

(3) DSO sub network operator computes the new average power imbalances and phase residual, updates its dual variables which reflects the imbalances, normally, it is called shadow price. The shadow price will be broadcasted to the associated actors.

(4) Termination condition checking, if the net power imbalance and phase inconsistency across all sub networks of the system is less than a small value, then it is balanced, otherwise, go to number one in step 2.

We simulate the proposed method in a distribution network. Fig. B.6 depicts the relevant loads and lines inside the network. Several EV fleet operators are regarded as the aggregated load and numbered as load 1, 2, 3, 4. Five sub-networks are defined. We consider the power line's power constraints as well the voltage limitations.

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