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A semi-distributed charging strategy for electric vehicle clusters[☆]

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ABSTRACT

Uncoordinated charging of electric vehicle (EV) clusters can lead to unanticipated surges in demand that strain the grid, hence reducing its reliability. To address this challenge, this paper proposes a semi-distributed control method for EV clusters charging where the decision-making process takes place locally, rather than relying on an external controller. The method ensures that charging demand can be fulfilled while achieving several goals, including following local renewable energy generation, pausing charging for transformer protection, and continuing charging progress in the absence of external information. The proposed method is validated through simulations and experimental tests during a public demonstration. The results demonstrate the functionality of the control method and show that it can effectively manage the charging of a cluster of EVs while reducing strain on the power grid.

1. Introduction

Electric vehicles (EVs) have gained significant attention in recent years due to their potential to reduce greenhouse gas emissions. Additionally, the increasing availability of renewable energy sources (RES) and advances in battery technology have made EVs more attractive to consumers, who are now able to charge their vehicles at home or at public charging stations. While the growth of the EV market is promising, it also presents new challenges for the electric power system as EVs will significantly increase electricity demand. According to the International Energy Agency, the number of publicly accessible slow and fast chargers can increase to 11 million by 2030 (International Energy Agency IEA, 2020), hence a large amount of EVs being charged uncoordinated by owners at their convenience would impose power deficit in the power system, and could cause instability issues (Calearo et al., 2019).

This has led to the development of various coordination strategies for EV charging and other generation types, including centralized, decentralized and distributed method (Han et al., 2018), depending on how the communication is carried out. Centralized method requires a central intelligence that sends the control signal to all components based on certain objectives. In EV charging domain, a centralized controller aiming at balancing the state of charge (SOC) of multiple EVs while enabling V2G services is designed in (Zabetian-Hosseini et al., 2022). The authors of (Liu et al., 2022) concentrate on minimizing the total user charging cost via power scheduling strategies according to user behaviors, and the control signals are also sent from a central operator.

Centralized methods can be effective in ensuring that the charging of the EV clusters is coordinated and optimized, but it could be challenging to implement the schemes in practice, since a dedicated communication system is required to collect large amount of data from all EVs and command them in real time. Besides the security of the system cannot be guaranteed as such a setup is not robust to the failure of the central agent. Therefore, decentralized control methods have been proposed to facilitate the coordination without explicit communication and improve robustness to failure. The authors of (Ziras et al., 2019) describe a decentralized stochastic control method for implicitly coordinating small-scale energy storage systems to provide primary frequency regulation without any exchange of information between the units; results show that the strategy increases system efficiency while guaranteeing a promising service accuracy. A fully decentralized control scheme is proposed in (Zhang et al., 2017), where a randomized autonomous control strategy is introduced in which EVs do not receive any common reference signal, ensuring reduced load variations to the grid. However, decentralized control often results in less optimal outcomes since the individual nodes have limited knowledge on the states and objectives of the other nodes for coordination (Han et al., 2018).

Compared to the above counterparts, the distributed control method is seen as a key to balance the robustness and optimality of a system. Typically, a distributed control method would require a central system

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to broadcast a common signal to all individuals, and each local unit independently handles the decision-making process thereafter. A hybrid control method of EV charging that combines both centralized and distributed method is introduced in (Vaya and Andersson, 2013), in this paper the two concepts are consecutively implemented in two steps to provide secondary frequency regulation. Also in frequency regulation field, authors in (Moghadam et al., 2016) designed a distributed method that all EVs monitor system frequency individually during contingency situation, in which the grid operator would spread out a signal to activate/deactivate the threshold-based switching algorithms of EVs according to the events. Research in (Zhang et al., 2014) proposed a distributed control approach based on pricing scheme, where EVs respond to a pricing signal from the central unit and act autonomously. However, the above distributed methods consider that all EVs are connected to the grid independently or assume a sufficiently high cluster limit. In both cases, full-power charging for all cars is available, which does not align with the practical reality that EVs charge in a cluster with limited capacity. An autonomously distributed control approach for EV parking lots management was described in (Striani et al., 2023; Striani et al., 2022), where the central intelligence dispatches pre-set power to all EV clusters. The pre-set power is decided based on information such as RES generation, user inputs and transformer loadings. Each EV cluster then operates in an autonomous manner locally. However, the paper limits the charger controller to only activate one plug at a time, which reduces the fairness of the charging sessions.

Although numerous studies have been conducted to achieve the best outcomes, the corresponding experimental validation is rarely touched upon, most of the control schemes are merely tested in a simulation environment. To achieve a practically well-functioning charging control strategy, a charging system consisting of two EV charger controllers has been built by Technical University of Denmark (DTU), integrating into its already existing Energy System Integration Lab – SYSLAB on Risø campus, for designing and testing the feasibility of the implemented charging strategies. This paper introduces a semi-distributed control approach which achieves both promising power sharing and robustness in diverse situations. The outcomes indicate that the developed mechanism is adaptable to different public charging stations. Validation has been carried out in both simulations and experimental tests in a public demonstration in SYSLAB on November 9th, 2022. This paper is organized as follows: The charging system infrastructure and functionality are explained in Section II. Section III describes the simulation model and introduces power allocation logics. The results are presented and discussed in Section IV, and Section V concludes the paper.

Table 1
Charging system overview.

Component	Value	Unit
Charger controller fuse limit	22	kW
PCC fuse limit	36.57	kW
PV panel (peak)	5	kW
PV emulator (peak)	20	kW
Wind turbine (peak)	10	kW
Adjustable load (peak)	40	kW

2. Charging system infrastructure

The charging system is developed in SYSLAB at DTU Risø campus. The system consists of two EV charger controllers, adjustable load, and renewable energy sources, as summarized in Table 1. Each charger controller possesses two outlets and controls the charging process for two EVs simultaneously. Four EVs were selected for the demonstration with information presented in Table 2. The fuse limit level of charger controllers is determined by standard EV charger rating, while the PCC fuse limit level is settled by the supply contract of the laboratorial system set up. Fig. 1 shows the system used during the public demonstration.

Fig. 2 shows how information is communicated in the system in a semi-distributed way. The whole system conducts the communication among an Amazon Web Service (AWS) cloud and four virtual aggregators (VA). VA is a local processor inside each outlet of the charger controller, it collects charging requests from the EV and sends the corresponding power signal back. AWS is a cloud platform which transfers information from Point of Common Coupling (PCC) to the system and relay communication among VAs.

One VA is assigned as a primary VA, which serves as the decision-making mind of the system, in this case it is VA_1. All charging requests from $VA_{2,3,4}$ will be sent to VA_1 through AWS cloud, together with the external information from PCC. External input from PCC comprises of available power from power grid and local renewable, as well as fuse limit of each charger controller and PCC. Then the primary VA processes the power allocation for all EVs and sends the power adjustment to each VA via AWS as well.

Compared to the usual centralized approach, this charging system completes the charging tasks in a semi-distributed way, where the failure of the cloud platform will not cause a total termination to all the

Fig. 1. The charging system demonstrated at DTU.

Table 2
Selected EV information.

EV	Max/min current	Max/min power	Battery capacity	Charging phase
EV_1 (Nissan LEAF)	32/6 A	7.36/1.38 kW	62 kWh	1 phase
EV_2 (Renault Zoe)	32/6 A	22.08/4.14 kW	42 kWh	3 phases
EV_3 (Nissan LEAF)	32/6 A	7.36/1.38 kW	62 kWh	1 phase
EV_4 (Renault Zoe)	32/6 A	22.08/4.14 kW	42 kWh	3 phases

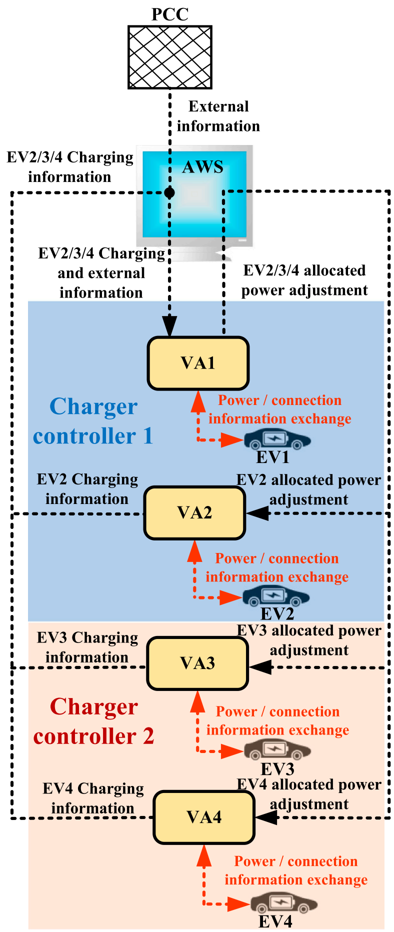


Fig. 2. Communicative architecture of the charging system.

participants. The cloud is behaving as an information transmitter without any decision-making responsibility. VA_1 instead, takes the role, and it will be taken over by the next VA if it breaks down. The system aims for a more secure and robust scenario with this semi-distributed implementation.

3. Charging system model development

3.1. Model development

A simulation model is developed in MATLAB/Simulink to reflect the architecture of the charging system and to investigate the charging behaviors in different scenarios. Fig. 3 showcases the role of each component; power reference represents the available power from PCC. Power allocation will be carried out in VA_1, and subsequently compared with measured power from each EV to create the corresponding power error, which is the expected power adjustment. The power error signal is provided to each VA, which is then processed by its own PI controller to ensure a smooth variation in power. The parameters of PI controllers are shown in Table 3.

Fig. 4 depicts the operation inside each EV, charging logics part decides whether an EV is ready to charge with the information of connection status, system load level and battery SOC level, only a system with sufficient space for charging as well as the EV is connected and not fully charged will result in a ready-to-charge status. The charging efficiency $\eta_{Charging}$ spans from 80% at minimum charging power (1.38 kW per phase) to 90% at 3.68 kW per phase with a linear progression based on experimental measurements (Calearo et al., 2021), charging power above that is assumed to have 95% efficiency. There is a time lag for an EV to really starting charging, the delay for each EV used is presented in Table 3 and is based on the behaviour of the experimental demonstration. It is worth mentioning that it also includes the time delays in relays among different components. The power variation of EVs is also subject to a certain ramp rate limit based on experimental tests in the lab (Sevdari et al., 2022).

3.2. Power allocation logics

One of the most important parts of this model is power allocation

Table 3
Parameter of charging system model.

Kp	Ki	Nissan LEAF ramp rate limit	Renault Zoe ramp rate limit	Time delay EV_1	Time delay EV_2	Time delay EV_3	Time delay EV_4
0.001	0.15	2.43 kW/s	1.05 kW/s	16 s	16 s	5 s	12 s

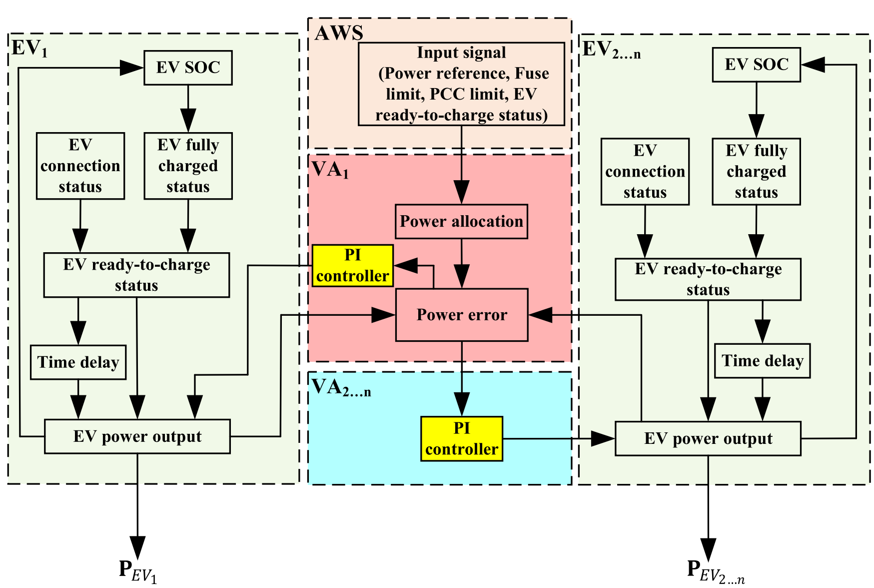


Fig. 3. Charging system model.

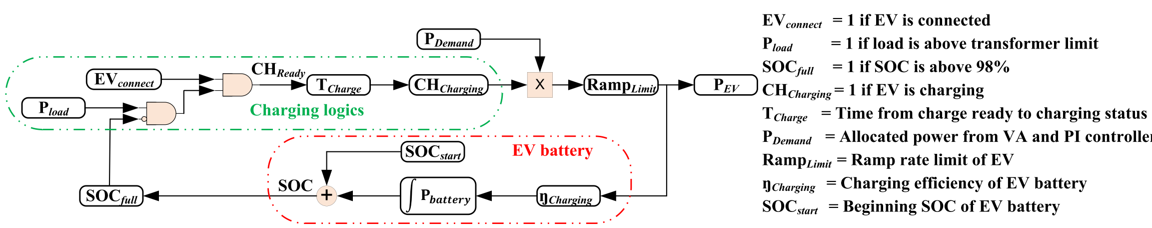


Fig. 4. EV operation.

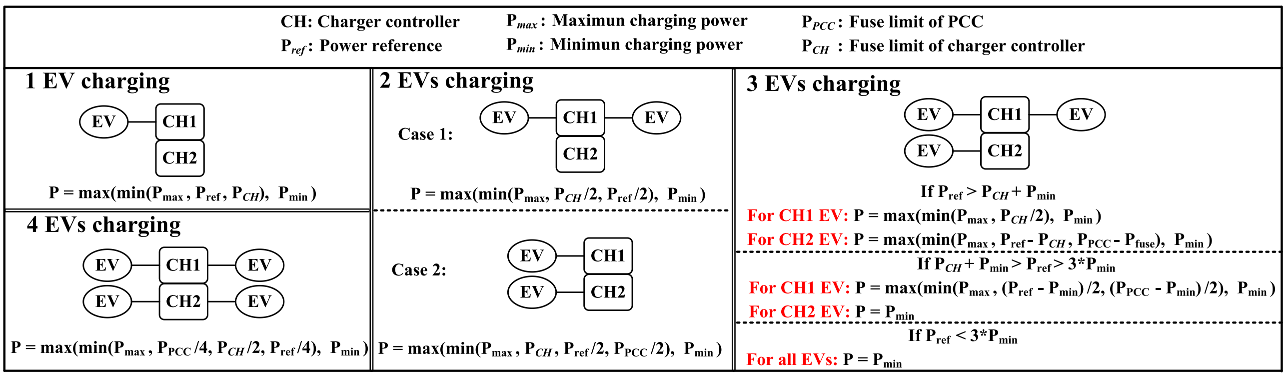


Fig. 5. Power allocation logics.

logics in VA_1, which is detailed in Fig. 5. The core purpose is to make sure the available charging power can be shared among connected EVs without breaching any fuse limits. In addition, the system is also designed to afford different scenarios: 1) Follow local renewable generation; 2) Protect the transformer if load level exceeds the limit; 3) Keep the constant charging level if the information from outside is lost.

Fig. 5 shows how power reference is shared to support different number of EVs connected. The power should be shared equally among requesters with at least minimum charging power. However, fuse limit and maximum charging power also restrict the allocated power. An example is when 2 EVs are connecting, fuse limit needs to be considered in this situation: if the EVs are connecting via the same charger controller, then the charger controller fuse limit will be imposed; while the PCC fuse limit will be applied if the EVs are separately connecting through two charger controllers. Since charger controller fuse limit is lower, the allocated power will also be restricted by a lower level if both EVs are connecting via the same controller.

A challenging circumstance is when 3 EVs are connected, which implies that 2 EVs will be sharing one charger controller and the other charger controller has the third EV plugged in. Hence, the charger controller fuse limit hinders equal allocation. In this case, the priority is to satisfy the first 2 EVs to the largest extent as the combined power request is larger from the network's perspective.

It is emphasized that the power reference represents the available power left after satisfying the local load, hence if the load in the system is too high to reach PCC fuse limit, charging sessions will be paused and charging power will decrease even from minimum power to zero.

4. Results and discussion

As briefly mentioned in Section I, simulations and experimental tests in a public demonstration were conducted for validation, and they present the functionality of the charging system in four scenarios, described in Table 4. The local load is set to zero in scenario 1, 2, and 4 to fully exploit how power sharing is operated, while scenario 3 will result in a high load spike that reaches the PCC fuse limit, leaving no space for charging. All EVs are assumed to start with 0% SOC for simulation as no full SOC were reached during the demonstration. A noteworthy point in scenario 2 is that RES is set as an additional generation together with the import from the grid, which guarantees that all EVs charging will achieve at least the minimum charging power even when RES is close to 0 kW.

Due to the hardware setup in the charger controllers at the time of the demonstration, all EVs are treated to possess 3-phase charging capability. Therefore, Nissan LEAF (single phase EV) will be allocated with 3-phase power, whereas only one phase will eventually get the power, which leads to 1/3 power for the receiver. A simple example is a Nissan LEAF and a Renault Zoe connecting to the same charger

Table 4
Scenario description.

Scenario	Description	Power reference	Time duration	Expectation
Scenario 1 (Power sharing)	The system is fully available for charging, the local load is set to zero.	36.57 kW	500–1300 s	EVs are expected to share available power equally subject to corresponding fuse limits.
Scenario 2 (RES following)	RES is considered as additional generation to the system with the local load set to zero.	RES power	1500–2400 s	EVs are expected to charge close to local RES production for maximum consumption.
Scenario 3 (Transformer protection)	The system will be fully occupied by the local load.	36.57 or 0 kW	2500–2900 s	EVs are expected to pause charging while the system is struggling with local demand.
Scenario 4 (Communication failure)	Information transfer from AWS cloud will be ceased, the local load is set to zero.	36.57 or 0 kW	3000 s – onwards	EVs are expected to continue charging without communication from the cloud.

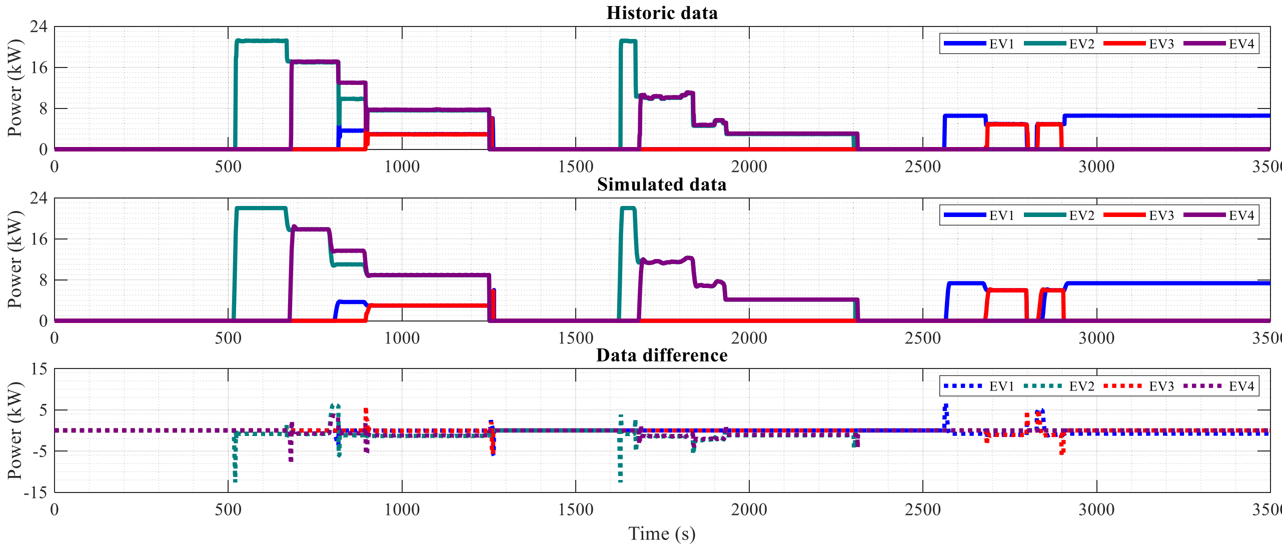


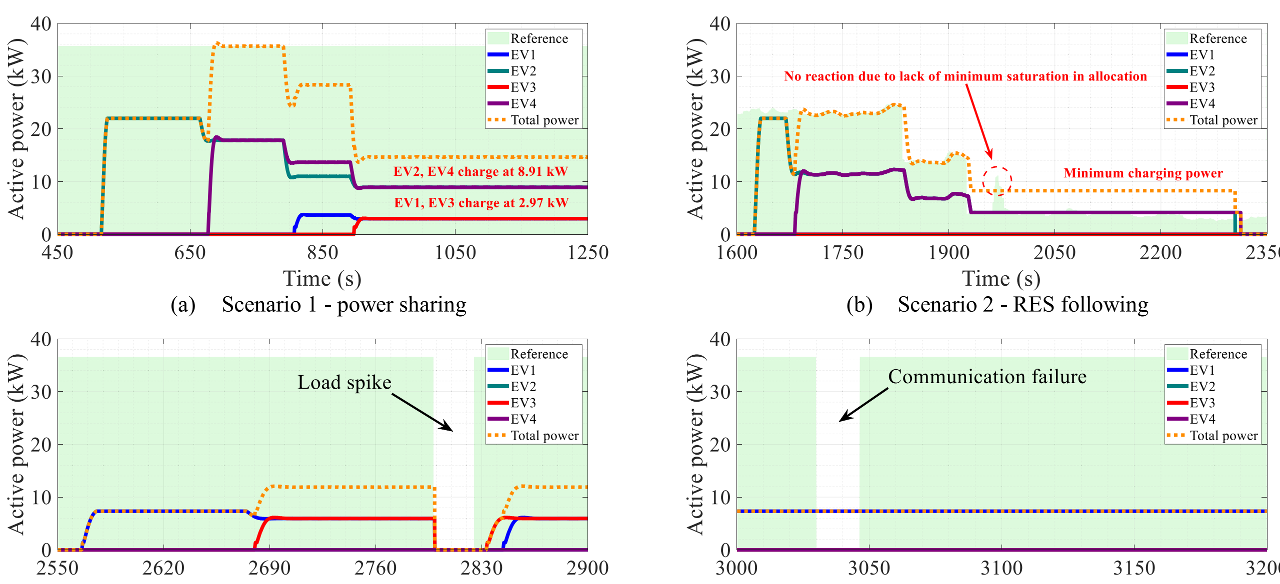
Fig. 6. Comparison of simulation and demonstration.

controller with enough power reference, each EV then will be allocated with 11 kW which is 50% of the charger controller fuse limit. However, this 11-kW power is distributed on 3 phases, resulting in only 3.67 kW for Nissan LEAF. This issue will be tackled in the future development.

Fig. 6 compares between the demonstration and model simulations in the four scenarios. The whole demonstration part lasted for one hour where four scenarios were displayed consecutively: each scenario requires certain EVs to be plugged in and out. It can be observed from the third plot in Fig. 6 that the developed model successfully captures the mechanism of the charging system with acceptable differences due to delay discrepancies and reactive power consumption during the demonstration. The average power differences between simulated data and historic data are −0.43 kW, −1.14 kW, −0.33 kW and −1.06 kW for EV_1, EV_2, EV_3 and EV_4 respectively.

The specifics of each scenario are shown in Fig. 7, where the four scenarios are presented individually in (a), (b), (c) and (d). Power sharing scenario is firstly operated, where four EVs are all connected consecutively. It is worth bringing attention that charging power will reduce every time when a new EV starts to charge, the reason lies in the space saving mechanism caused by equal sharing logic. The charging power is kept at 22 kW when EV_2 is firstly plugged in due to the fuse limit of charger controller, then the individual charging power reduces to 17.8 kW when EV_4 participates, which is restricted at 50% of PCC fuse limit. The charging power later reduces to unequal distribution after EV_1 and EV_3 take part since they can only be charged in single-phase. The model is established as each charger controller has a three-phase EV and a single-phase EV plugged in, while single-phase EV is treated as a three-phase consumer, the power received is only 1/3. In the case of 4 EVs connecting, each of them gets 1/4 of PCC fuse limit, and single-phase EVs lose further 2/3 as in Fig. 7(a).

An intriguing feature to note in scenario 1 is when 3 EVs are connected at around 850 s, as mentioned previously the system will take preference of the fully occupied charger controller, hence EV_1 and EV_2 will be allocated with 22 kW in the first place, and EV_4 gets the rest 13.67 kW. While EV_1 is a single-phase EV, it will charge at 1/3 level of EV_2, leading to three different charging power levels.



(a) Scenario 1 - power sharing
(b) Scenario 2 - RES following
(c) Scenario 3 – transformer protection
(d) Scenario 4 – communication failure

Fig. 7. Simulation results of four scenarios.

Fig. 7(b). depicts the charging process in RES following scenario, where only the two three-phase EVs are participating. The objective is to charge EVs with additional RES rather than extracting energy from the grid as much as possible, thus the power available for allocation is renewable generation. The model manages to adapt EV consumption to a fluctuating input, while also keeping EVs at least the minimum charging level if RES does not suffice.

There is a RES generation spike in red circle for around 10 s where the charging power doesn't follow, the cause of this is the power allocation logic in VA_1, which does not include minimum power saturation during the demonstration. When RES input is lower than the minimum charging power, VA_1 will still allocate an unacceptably low value, whereas charging power will be locked at the P_{min} due to the EV characteristics. Then the calculated power error will always be negative, indicating the system is demanding EVs to continue reducing the power. The error is consequently integrated by PI controllers, the longer it lasts, the larger the integration will be until it reaches maximum error (set as $-P_{max}$). Therefore, a small and short spike is too weak to offset the already integrated negative power error, leading to a non-reaction scenario. The adjustment was implemented in the charger controller and Simulink model after the demonstration; however, this simulation switches it off for the sake of replication.

Fig. 7(c). showcases the charging process of two single-phase EVs in transformer protection scenario, where a local load was set, causing the power reference to hit bottom. In this case, all the charging sessions are paused due to the load spike, and later resume after the load is lifted to protection network transformer. On the contrary, Fig. 7(d) presents a different charging behavior when experiencing power reference drop. In communication failure scenario, the power reference reduces to zero due to a loss of signal from AWS cloud, hence the model proceeds the process without any input, keeping the previous charging level according to the logics. Even though power reference is also zero in transformer protection scenario, there is still other signal input such as charging ready status, whereas in communication failure the system cannot receive any information, which differentiates the allocation logics.

5. Conclusion

This paper presents a semi-distributed control method for charging EV clusters. The proposed power sharing logic ensures that all EVs charging requests can be satisfied within the system capacity. To validate the effectiveness of the system setup, experimental tests were conducted during a public demonstration, as well as a simulation model to evaluate the system performance. The results show similarities between the two with very limited differences of less than 1 kW on average. Furthermore, the applicability of the method was tested across four different scenarios, demonstrating its wide suitability from both optimal and robust perspectives.

In the future, the charging system will be implemented into a real parking lot on DTU Risø campus with three charger controllers. And this semi-distributed approach will improve to a fully distributed system where decision-making process takes place in every local VA rather than a primary VA. Power scheduling mechanism based on user inputs will also be investigated to achieve a more efficient coordination of the parking lot.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

The authors do not have permission to share data.

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