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A Network-Constrained Rolling Transactive Energy Model for EV Aggregators Participating in Balancing Market

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ABSTRACT The increasing adoption of renewable energy sources increases the need of balancing power. The security concerns of the distribution system operators are increasing due to fast adoption of distributed energy resources (DERs). So far, various operational models are proposed to manage the DERs for economic benefit. However, there is lack of an efficient operational model that balances the security, market, and uncertainty management. With the focus on the aggregator's operation, this paper has developed an operational model for continuous operation of aggregators interactively with the grid operators. A rolling optimization model is developed to manage the uncertainties from prediction errors. The network security is ensured continuously through an iterative price negotiation process between the distribution network operator and the aggregators. The optimality of the solution is guaranteed by convexification of the mixed integer formulation.

INDEX TERMS Rolling window, distributed energy resources (DERs), aggregator, balancing market, transactive energy, decentralized operation.

ACRONYMS

BM	Balancing market	E_b [kWh]	Capacity of battery
DAM	Day-ahead market	$SOC_{init}, SOC^{min}, SOC^{max}, SOC_{des}$ [%]	Initial, minimum, maximum state of charge (SOC), and desired SOC, respectively
NC	Network constraints	p^{MaxCh}, p^{MaxDis} [kW]	Maximum charging and discharging power of EV respectively
TE	Transactive energy	c_d [Dkk]	Degradation costs
UR/DR	up-regulation/down-regulation respectively	c_{bat} [Dkk]	EV battery capital cost

PARAMETERS

i, j, k, r, g	Time slot index, aggregator index, electric vehicle (EV) number index, rolling optimization process index, and bus no index, respectively	L_{ET} [kWh]	battery life in terms of energy throughput
μ^{DA}, μ^{BM} [Dkk/kWh]	Predicted DAM and BM price	L_c, DoD	Cyclic life and depth-of-discharge respectively
η_{Ch}, η_{Dis} [%]	Charging/discharging efficiency	m^{up}/m^{down}	Upper boundaries of UR and DR respectively
T_k^{ST}, T_k^{ST} [h]	The start and end charging time of the k^{th} EV	N_{bus}	Total number of buses of the system
N_{EV}, N_{RBM}, N_{RDA}	Total number of EVs, rolling window, and length of rolling window	Mg	Participation factor representing the participation preference of each EV owner.

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U^{max}, U^{min}	Minimum and maximum voltage limits
U^0	Initial voltage of the buses of the network
P_{trans}^{Max}	Capacity of transformer
J_{21}^{-1}	Submatrix of the inverse Jacobian.
β	Step length, set as 0.4 initially
ω	Convergence standard, set as 0.005

VARIABLES

δ^a, δ^b	Binary variables representing charging and discharging modes respectively
P^{Ch}, P^{Dis} [kW]	Charging and Discharging schedules of an EV, respectively
δ^1, δ^2	Binary variables flagging the UR and DR operation
P^{up}, P^{down} [kW]	Powers for UR and DR operation, respectively. Both are positive values always.
δ^3	The battery is in charging mode. $\delta^3(P^{Ch} - P^{Dis} - \delta^1 P^{up} + \delta^2 P^{down}) \geq 0$
δ^4	The battery is in discharging mode. $\delta^4(P^{Ch} - P^{Dis} - \delta^1 P^{up} + \delta^2 P^{down}) \leq 0$
$z^1 = \delta^1 \delta^3 P^{up}$ [kW]	An EV provides UR and in charging mode
$z^2 = \delta^2 \delta^3 P^{down}$ [kW]	An EV provides DR and in charging mode
$z^3 = \delta^1 \delta^4 P^{up}$ [kW]	An EV provides UR and in discharging mode
$z^4 = \delta^2 \delta^4 P^{down}$ [kW]	An EV provides DR and in discharging mode
P^{FCh}, P^{FDis} [kW]	The optimal charging and discharging schedules of an EV in DAM respectively
P^{BM} [kW]	The optimal schedule of the aggregator for participating BM
P^{ChN}, P^{DisN} [kW]	New schedules after TE deviating from P^{BM} due to NC
P^{DSO} [kW]	The optimal schedule of DSO in TE market
λ [dkk/kWh]	Virtual price signal
$P_{g,i,j}^{ChN*}, P_{g,i,j}^{DisN*}$ [kW]	New schedules after TE deviating from P^{BM} due to NC of bus g associated with aggregator j at time interval i
$P_{g,i,j}^{DSO*}$ [kW]	The optimal schedule of DSO after TE at bus g associated with aggregator j at time interval i

I. INTRODUCTION

The Paris agreement underlines the urgency of decarbonizing the current energy sector [1]. With the integration of

distributed energy resources (DERs) such as solar photovoltaics (PV), batteries, and electric vehicles (EVs), the distribution system operation becomes more complex and dynamic. Congestion and voltage constraints are the main security challenges to the system operators to ensure a safe operation, while the flexibility in the new type of demand provides the system operator possibilities to address these challenges [2]. Small prosumers usually lack knowledge, information and resources to optimize their assets, which naturally make their operation best conducted through a representative party such as aggregator. The EV aggregator (EVA) is actually an intermediary who manages the energy consumption of total subscribed EV owners.

Attention has been devoted to vehicle charging, demonstrating various algorithms to optimize EV charging strategies considering uncertainties in prices and energy demand [3], [4], or network constraints (NCs) [5], [10]. In [6], the optimal charging strategies for EVs from either the perspective of DSO or commercial parties were proposed. A close-loop EV charging strategy for loading serving entity was proposed in [7] which can adjust the real-time prices in response to EV consumers' behavior. To maximize the EVs' profits in both DAM and reserve market, a linear programming (LP) model was studied in [8]. With the increasing number of EVs, the day-ahead market (DAM) price may be influenced by the EV charging demand which formulated as an aggregative game model in [9]. In [10], a EV charging station model is proposed considering the network reinforcement cost.

To make the best use of EVs, optimal scheduling of EVA was investigated in [12]–[14] where the EVAs acted as a balancing responsible party (BRP). In [12], the optimal operating strategy of EVA participating in the DAM, intraday market, and BM was proposed considering the stochastic behavior on vehicle parking patterns and battery lifecycle costs. Authors in [13] proposed an optimal schedule for EV charging taking the battery discharging degradation costs, the network constraints and different EV usage behaviors into account. A co-optimization approach for both customer and system operator's objectives was presented in [14].

It should be noted that the above energy scheduling methods are all based on the perspective of one party with a centralized optimization problem. In this model, the NC were managed either by the aggregator or the distribution system operator (DSO). For example, a distribution locational marginal price was obtained centrally and broadcasted by the DSO to alleviate the congestion problem in [5]. This type of model makes it hard to guarantee the customers' willingness to participate and ensure resources are available to respond, the fairness of the price can be questioned due to the special network structure in distribution grids.

Regarding the management of uncertainty and reduction of the impact of prediction errors robust optimization has been adopted in the energy scheduling optimization, e.g. [17]. Robust optimization only leads to conservative actions but not the uncertainly level. Rolling window optimization

(RWO) was introduced in the literature to utilize the latest information, and thus reduce uncertainty [18]. The EVs charging schedule in the DAM considering their impact on the power system unit commitment schedule, was formulated as a mixed-integer linear programming (MILP) in [19] through a day-by-day rolling analysis. Taking the advantage of RWO and model predictive control, a real-time microgrid dispatch for a combined cooling, heating, and power grid was presented in [20].

Considering the above mentioned work, this paper further develops the network constrained transactive energy (NCTE) concept [15], [16], [21] by taking the advantage of RWO in uncertainty handling for real-time operation and convexification of the aggregators' model to ensure optimality. The framework enables the participation of EVAs in the Nordic DAM and balancing market (BM) by optimally scheduling EVAs, considering the latest demand status and distribution system constraints. The technical improvement in comparison to the previous work is fourfold: 1) RWO method is applied for optimizing the operational strategy of each aggregator to reduce the impacts of electricity price prediction errors; 2) The battery operating cost is modeled and considered in the optimization problem formulation; 3) Taking the option of vehicle to grid (V2G) into account, a new bi-linear optimization model for EVA is proposed which can be applied both for DAM as well as BM; 4) A convexification method is developed to ensure the convexity of the formulation.

The organization of this paper is as follows. In Section II, the Nordic market structure and the RWO framework of EVA are introduced. In Section III, the mathematical modeling of the aggregators' optimal operational strategy in the DAM and BM are presented at first, then the procedure for obtaining the TE (transactive energy) solution using distributed optimization is specified. The simulation results and discussions are given in Section IV. Section V presents the conclusions.

II. MARKET PARTICIPATION PROCEDURE FOR EVA

In this section, the structure of Nordic electricity market is introduced at first. Thereafter, the application of RWO in each market is specified. The relation among each player in TE and the overall optimization framework of the aggregator is given in the end. In this work, the problem formulation does not include network utilization tariffs nor taxes. Including these would negatively affect the profitability of V2G.

A. NORDIC MARKET STRUCTURE

In Northern Europe, the power system has main five distinct markets: financial market, DAM, intraday market (IM), BM, and ancillary services market [22]. The first three markets are operated by Nord Pool while the TSOs maintain the system balance through the last two markets [23]. DAM and BM is operated as a pool, while IM is a bilateral market. Because historical price data from bilateral contracts are not publicly available, IM modelling is usually not done. This study focuses on the operation of the aggregator in the DAM and BM.

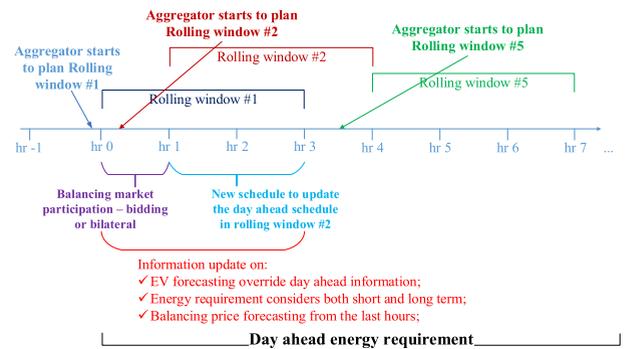


FIGURE 1. Rolling procedure for BM participation.

B. EVA OPERATION IN MARKET

We consider the EVA will first operate in the DAM. In the DAM, the EVA will estimate the entire day's energy requirement of the EVs under subscription, the past customs, and forecasted electricity prices to schedule the energy requirement. This energy requirement is rather primitive, with varying accuracy according to the actual operating time situation, which certainly will not be close to be optimal. No matter what optimization technique it is used for DAM participation, deviation in the electricity price, EV availability, and the expected energy requirements will occur to various degrees which need be corrected when the time is close to the actual operating hours by different parties depending on the mechanisms and incentives. There are different possibilities in the current market framework for the energy providers to correct their own imbalance for better economy before the actual operating hours, e.g. IM. In this work, we consider EVAs will sell their imbalance as a service to the grid operator.

C. RWO DESIGN FOR BALANCING MARKET

Due to the large integration of renewable energy, as the hour of operation approaches, the BM's price is likely to deviate from the DAM price. The BM begins when the day starts. EVA starts planning participation in the BM in the hour before the operating hour. The RWO time window is 3 hours here, but it can be stretched. The proposed RWO method for aggregators participating in BM is illustrated in Fig. 1.

In this framework, the EVA will plan for the next three hours BM participation given the updated information from the EV availability, updated state of charge (SOC) of EV batteries, charging constraints (e.g. charger type) and regulating power price. It is assumed that we have a better prediction of the price in the BM for the next coming hour than the following two hours, therefore, only the first hour decision is taken for BM participation. In the next hour, the EVA will start the same process for the coming time window planning. The process will continue which makes it a rolling-window-based operation.

The RWO takes advantage of the fact that the prediction error for BM prices is reduced closer to the hour of operation.

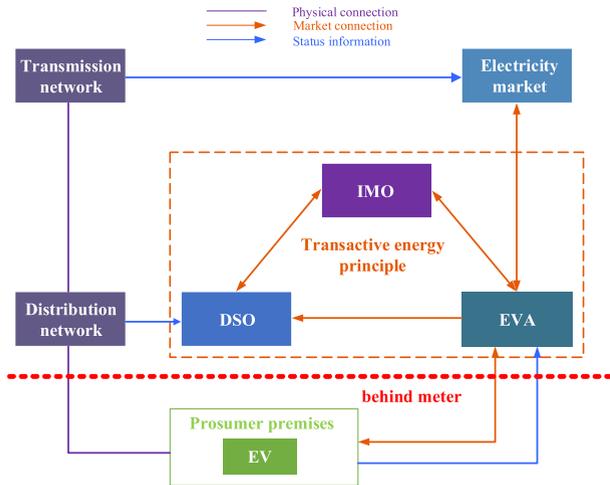


FIGURE 2. Electricity market (DAM, BM) of EVA in the distribution network.

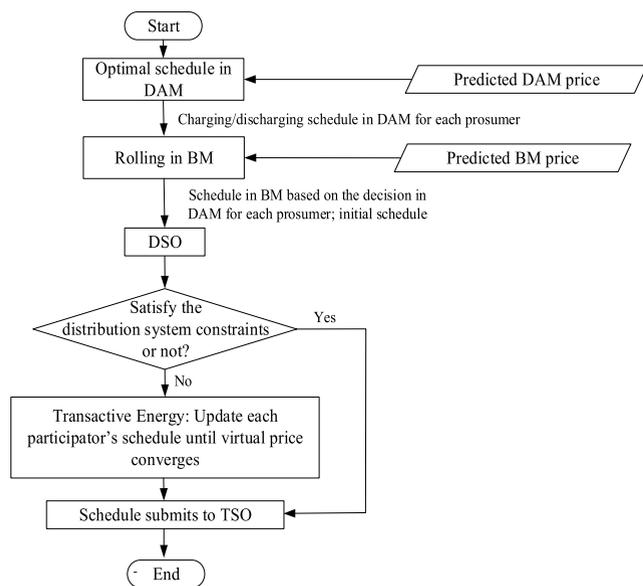


FIGURE 3. The optimization framework for the aggregator.

D. TRANSACTIVE ENERGY FRAMEWORK

The principle of TE is shown in Fig. 2, which is similar to [21]. DSO and EVA is interacting through an independent market operator (IMO) for exchanging a virtual price signal. The total EVs can be viewed as a time-varying virtual storage (TVVS) model.

E. OVERALL OPTIMIZATION FRAMEWORK FOR EVA

Considering the constraints from the DSO, the optimization framework for the EVA should be modified to incorporate the TE. The overall flowchart is shown in Fig. 3. In this study, assumptions are adopted as follows: 1) EVAs can receive information of energy needs, prediction of the market prices for the DAM and BM participation. This can be guaranteed with the current market transparency and the registered information of the public and private chargers; 2) The up and down

regulation power supplied by EVA will be taken by TSO and fully activated by the TSO within one hour; 3) Distribution line capacity is not considered, and the power factor of the load is 1. This is verified by analyzing over 2000 smart meter data over 1.5 years in Denmark.

III. MATHEMATICAL FORMULATION

In this section, the mathematical formulation of the problem considering battery operating costs (BOCs) for EVAs in the DAM and BM is first presented. Secondly, the EVA's and DSO's objectives when the network security constraints are violated are introduced. Then, the overall optimization problem is formulated as a social welfare maximization (and cost minimization) problem. The distributed optimization method is presented at last for decomposing the problem and solving it in a decentralized manner.

A. OPTIMIZATION IN THE DAM

The EV prosumers are heterogeneous, having different driving patterns, charging/discharging efficiency, etc. In this work, the prosumers' behaviors are considered as 1) Different prosumers' daily driving route and working hour are represented by the different initial SOC, charging/discharging start and end time. 2) Since different prosumers may choose different types of EVs, the EV capacities and maximum charging/discharging power are modeled to be different.

Since the V2G functionality is expected to be active in the DAM, two binary variables, $\delta_{k,i}^a$ and $\delta_{k,i}^b$, are introduced to indicate the EV operating charging and discharging status at a particular hour. Then, the proposed model is written in the following.

$$\min \sum_{k=1}^{N_{EV}} \sum_{i=T_{st}(k)}^{T_{end}(k)} (P_{k,i}^{Ch} - P_{k,i}^{Dis}) \lambda_i^{DA} + c_{d,k} P_{k,i}^{Dis} \quad (1)$$

$$\text{s.t. } \delta_{k,i}^a, \delta_{k,i}^b \in \{0, 1\} \quad (2)$$

$$\delta_{k,i}^a + \delta_{k,i}^b \leq 1 \quad (3)$$

$$0 \leq P_{k,i}^{Ch} \leq \delta_{k,i}^a P_k^{MaxCh} \quad (4)$$

$$0 \leq P_{k,i}^{Dis} \leq \delta_{k,i}^b P_k^{MaxDis} \quad (5)$$

$$SOC_{k,i+1} = SOC_{k,i} + (P_{k,i}^{Ch} \eta_{Ch} - P_{k,i}^{Dis} \eta_{Dis}^{-1}) E_b^{-1} \quad (6)$$

$$SOC_{k,1} = SOC_{init}^k \quad (7)$$

$$SOC^{\min} \leq SOC_{k,i} \leq SOC^{\max} \quad (8)$$

$$SOC_{k,end} \geq SOC_{des} \quad (9)$$

The energy level of EV battery for each time slot is calculated by Eq. (6) and limited by Eq. (8). The expected SOC of each EV should be met at the end of the charging period is described as Eq. (9). The above problem is formulated as MILP model and can be solved with the conventional solver which will be introduced at the end of this section.

B. BATTERY OPERATING COST (BOC)

The battery lifetime is usually counted by the number of cycles and is highly related to the depth of discharging.

In [13], the battery discharging degradation cost has been specified. In this work, the battery operating cost in addition to energy purchasing cost considering both the impacts of charging and discharging at an average DoD is formulated as follow:

$$c_d = c_{bat} L_{ET}^{-1} \quad (10)$$

$$L_{ET} = L_c E_b DoD \quad (11)$$

where Cbat is 373 Euro/kWh.

C. RWO IN BALANCING POWER MARKET

The up and down regulating power is decided in the BM through RWO in this work considering the settled schedule in the DAM. Some binary variables are defined to indicate the operational status of the battery and the type of regulation provided. It should be noticed that the above optimization problem contains bi-linear terms which make the problem non-convex. This intractable problem can be resolved by introducing extra artificial variable $z_{k,i,r}^1$ to $z_{k,i,r}^4$. This is the so-called big M method [24]. Through the big M linearization, the MILP formulation for EVA's optimal schedule in BM can be expressed in the following.

$$\min \sum_{j \in \Omega_j} \sum_{r=1}^{N_{RBM} N_{EV}} \sum_{k=1}^{T_k^{end}} \sum_{i=T_k^{st}} \left[\left(z_{k,i,r}^2 - z_{k,i,r}^1 + z_{k,i,r}^4 - z_{k,i,r}^3 \right) \lambda_{i+(r-1)N_{RL}}^{BM} + c_{d,k} \left(\delta_{k,i,r}^4 \left(P_{k,i}^{FCh} - P_{k,i}^{FDIs} \right) - z_{k,i,r}^3 + z_{k,i,r}^4 \right) \right] \quad (12)$$

$$\text{S.t. } \delta_{k,i,r}^1, \delta_{k,i,r}^2, \delta_{k,i,r}^3, \delta_{k,i,r}^4 \in \{0, 1\} \quad (13)$$

$$\delta_{k,i,r}^1 + \delta_{k,i,r}^2 \leq 1 \quad (14)$$

$$\delta_{k,i,r}^3 + \delta_{k,i,r}^4 = 1 \quad (15)$$

$$0 \leq P_{k,i,r}^{Up} \leq P_k^{MaxCh} + P_{k,i}^{FCh} - P_{k,i}^{FDIs} \quad (16)$$

$$0 \leq P_{k,i,r}^{Down} \leq P_k^{MaxCh} - P_{k,i}^{FCh} + P_{k,i}^{FDIs} \quad (17)$$

$$0 \leq \delta_{k,i,r}^3 \left(P_{k,i}^{FCh} - P_{k,i}^{FDIs} \right) - z_{k,i,r}^1 + z_{k,i,r}^2 \leq P_k^{MaxCh} \quad (18)$$

$$-P_k^{MaxDis} \leq \delta_{k,i,r}^4 \left(P_{k,i}^{FCh} - P_{k,i}^{FDIs} \right) - z_{k,i,r}^3 + z_{k,i,r}^4 \leq 0 \quad (19)$$

$$SOC_{k,1,1} = SOC_{init}^k \quad (20)$$

$$SOC_{k,1,r} = SOC_{k,N_{R+1},r-1} \quad r \in [2, N_{RDA}] \quad (21)$$

$$SOC_{k,i+1,r} = SOC_{k,i,r} + \left[\left(\delta_{k,i,r}^3 \left(P_{k,i}^{FCh} - P_{k,i}^{FDIs} \right) - z_{k,i,r}^1 + z_{k,i,r}^2 \right) \eta_{Ch} + \left(\delta_{k,i,r}^4 \left(P_{k,i}^{FCh} - P_{k,i}^{FDIs} \right) - z_{k,i,r}^3 + z_{k,i,r}^4 \right) \eta_{Dis}^{-1} \right] E_b^{-1} \quad (22)$$

$$SOC_k^{\min} \leq SOC_{k,i,r} \leq SOC_k^{\max} \quad (23)$$

$$SOC_{k,end,r} = SOC_{des} \quad (24)$$

The constraints added to the formulation due to the utilization of big M linearization are written as follows [25]:

$$0 \leq z_{k,i,r}^1 \leq P_{k,i,r}^{up} \quad (25)$$

$$m_k^{up} = P_k^{MaxCh} + P_{k,i}^{FCh} - P_{k,i}^{FDIs} \quad (26)$$

$$-z_{k,i,r}^1 - \left(\delta_{k,i,r}^1 + \delta_{k,i,r}^3 \right) \leq -P_{k,i,r}^{up} + 2m_k^{up} \quad (27)$$

$$-z_{k,i,r}^1 \leq -P_{k,i,r}^{up} + m_k^{up} \quad (28)$$

$$z_{k,i,r}^1 - m_k^{up} \delta_{k,i,r}^1 \leq 0 \quad (29)$$

$$z_{k,i,r}^1 - m_k^{up} \delta_{k,i,r}^3 \leq 0 \quad (30)$$

$$0 \leq z_{k,i,r}^1 \leq P_{k,i,r}^{down} \quad (31)$$

$$m_k^{down} = P_k^{MaxCh} - P_{k,i}^{FCh} + P_{k,i}^{FDIs} \quad (32)$$

$$-z_{k,i,r}^2 + m_k^{down} \left(\delta_{k,i,r}^2 + \delta_{k,i,r}^3 \right) \leq -P_{k,i,r}^{down} + 2m_k^{down} \quad (33)$$

$$-z_{k,i,r}^2 \leq -P_{k,i,r}^{down} + m_k^{down} \quad (34)$$

$$z_{k,i,r}^2 - m_k^{down} \delta_{k,i,r}^2 \leq 0 \quad (35)$$

$$z_{k,i,r}^2 - m_k^{down} \delta_{k,i,r}^3 \leq 0 \quad (36)$$

Similar 'big M constraints' should also be added regarding $z_{k,i,r}^3$ and $z_{k,i,r}^4$ following the format in (25)-(36). Due to the paper length limitation, this part is omitted. It should be noticed that the schedule settled in the DAM is a contract of purchase instead of real-time delivery. Hence, it is possible to 'update' the EVs' schedules in the BM which correspond to the new boundary described in (16) and (17). The final schedule of each EV after the BM should be allocated to its corresponding bus so that the DSO's constraints can be considered. In this sense, the unconstrained schedule is defined as $P_{g,i}^{BM}$ which is the aggregated schedule of each bus g at time i .

D. EVA's OPTIMAL SCHEDULE

The interest of the EVA is to minimize cost of energy in the market. However, due to system constraints, it has to update its own schedule to meet the DSO's requirements, which incurs deviations from its optimal schedule. The willingness of EVAs to shift their schedule is incentivized by the virtual price signal released by the IMO which will be explained in section III. F to G. The new optimization problem for an aggregator is formulated as follows:

$$A_j = \min \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} \left(P_{g,i,j}^{ChN} - P_{g,i,j}^{DisN} - P_{g,i,j}^{BM} \right)^2 M_{g,i,j} \quad (37)$$

$$\text{S.t. } 0 \leq P_{g,i,j}^{ChN} \leq P_g^{MaxCh} \quad (38)$$

$$0 \leq P_{g,i,j}^{DisN} \leq P_g^{MaxDis} \quad (39)$$

$$SOC_{g,i+1,j} = SOC_{g,i,j} + \left(P_{g,i,j}^{ChN} \eta_{Ch} - P_{g,i,j}^{DisN} \eta_{Dis}^{-1} \right) E_b^{-1} \quad (40)$$

$$SOC_{g,1,j} = SOC_{init}^g \quad (41)$$

$$SOC_{g,end,j} = SOC_{des}^g \quad (42)$$

$$SOC_k^{\min} \leq SOC_{k,i} \leq SOC_k^{\max} \quad (43)$$

A large $M_{g,i,i}$ indicates a stronger willingness to participate in the BM. In this work, it is assumed that $M_{g,i,i}$ equals to 1 which means that all the EV have the same willingness

to participate in the BM. It should be noticed that the binary variables are neglected in the above formulation which is a convex optimization problem. The mathematical proof of convexification is given in the following.

Proof: Assume $P_t^+ \geq 0$ and $P_t^- \geq 0$ are the optimal charging and discharging solution satisfying $P_t^+ P_t^- \neq 0$, for any $t \in [1, N]$. N is the total number of time slots. Let $Q_t^+ = P_t^+ - \varepsilon$ and $Q_t^- = P_t^- - \varepsilon \eta_+ \eta_-$ to be another solution while ε represents a small positive value. Those two solutions yield the same change of state of charge as:

$$Q_t^+ \eta_+ - \frac{Q_t^-}{\eta_-} = P_t^+ \eta_+ - \frac{P_t^-}{\eta_-} \quad (44)$$

Considering the quadratic objective function in (37), the optimality does not stand if the following condition is met:

$$\sum_{t=1}^N (Q_t^+ - Q_t^-)^2 < \sum_{t=1}^N (P_t^+ - P_t^-)^2 \quad (45)$$

$$\Rightarrow \sum_{t=1}^N (Q_t^+ - Q_t^- + P_t^+ - P_t^-) (Q_t^+ - P_t^+ - Q_t^- + P_t^-) < 0 \quad (46)$$

Taking $Q_t^+ = P_t^+ - \varepsilon$ and $Q_t^- = P_t^- - \varepsilon \eta_+ \eta_-$ into (46), we can then obtain:

$$\sum_{t=1}^N [(2P_t^+ - 2P_t^-) \varepsilon (1 - \eta_+ \eta_-)] > \varepsilon^2 (1 - \eta_+ \eta_-)^2 \quad (47)$$

In reality, the efficiencies are lower than 1, in other words, $\varepsilon(1 - \eta_+ \eta_-) > 0$. So (47) can be rewritten as:

$$\sum_{t=1}^N (2P_t^+ - 2P_t^-) > \varepsilon (1 - \eta_+ \eta_-) > 0 \quad (48)$$

As described in (40)-(43), there is a desired SOC level at the end of the scheduling which can be rewritten as follows:

$$SOC_{end} = SOC_{initial} + \sum_{t=1}^N (P_t^+ \eta_+ - P_t^- \eta_-^{-1}) E_b^{-1} \quad (49)$$

$$\Rightarrow \sum_{t=1}^N (P_t^+ \eta_+ \eta_- + P_t^-) = (SOC_{end} - SOC_{initial}) E_b \eta_- > 0 \quad (50)$$

$$\sum_{t=1}^N (P_t^+ - P_t^-) > \sum_{t=1}^N (P_t^+ \eta_+ \eta_- - P_t^-) > 0 \quad (51)$$

It can be seen that the assumption does not stand and the convexification of the original problem holds.

E. TARGET OF DSO

The responsibility of DSO is to transport the energy demand of each aggregator while ensuring the overall operational schedule meets the distribution system constraints. DSO's optimization problem can be written as follows:

$$D = \min \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} [P_{g,i}^{DSO} - \sum_{j=1}^{N_{agg}} P_{g,i,j}^{BM}]^2 \quad (52)$$

$$\text{S.t. } -P_{trans}^{Max} \leq P_{g,i}^{DSO} \leq P_{trans}^{Max} \quad (53)$$

$$U_{g,i}^{\min} \leq U_{g,i}^0 - J_{21}^{-1} P_{g,i}^{DSO} \leq U_{g,i}^{\max} \quad (54)$$

In (54), there is an approximation that assumes a constant power factor. This approximation method has been demonstrated to be an effective way of calculating the voltage deviations in [15], [26] and thus applied in this work.

F. SOCIAL WELFARE MAXIMIZATION

It can be seen from the previous explanation that both the EVAs and the DSO are wish to minimize their costs while meeting the systems' constraints. From a social welfare point of view, this integrated optimization problem can be formulated as follows:

$$\min \sum_{j=1}^{N_{agg}} \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} [A_j (P_{g,i,j}^{ChN}, P_{g,i,j}^{DisN}) + D] \quad (55)$$

$$\text{S.t. } (38) - (43), (53), (54)$$

$$P_{g,i}^{DSO} = \sum_{j=1}^{N_{agg}} (P_{g,i,j}^{ChN} + P_{g,i,j}^{DisN}) \quad (56)$$

It can be seen that (56) is the global constraint for the optimization problem of DSO and aggregators.

G. DISTRIBUTED ALGORITHM FOR TE REALIZATION IN THE DISTRIBUTION SYSTEM

Eq. (56) can be split into two single objective functions using Lagrange Multipliers, λ , which is also the virtual price signal [27], [28]. The Lagrangian function of (55) with coupling constraint (56) can then be formulated in the following.

$$\begin{aligned} L(\lambda, P^{ChN}, P^{DisN}, P^{DSO}) &= \sum_{j=1}^{N_{agg}} M_j (P_j^{ChN}, P_j^{DisN}) \\ &+ D(P^{DSO}) + \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} \lambda_{g,i} \\ &\times \left[\sum_{j=1}^{N_{agg}} (P_{g,i,j}^{ChN} + P_{g,i,j}^{DisN}) - P_{g,i}^{DSO} \right] \end{aligned} \quad (57)$$

In order to solve the above problem, a distributed optimization algorithm [26], [27] is applied to decompose the problem so that the complexity will be greatly reduced. The EVA and DSO will optimize their own schedules but with mutual interests which are linked by the λ . Then, the EVA's and DSO's optimization problem can be rewritten respectively in the following.

$$\min A_j (P^{ChN}, P^{DisN}) + \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} \lambda_{g,i} (P_{g,i,j}^{ChN} + P_{g,i,j}^{DisN}) \quad (58)$$

TABLE 1. EV battery parameters [33], [34].

EV Type	E_b	SOC^{\min}	SOC^{\max}	$P^{\max Ch}/P^{\max Dis}$	η_{Ch}/η_{Dis}	L_c	DoD
1	14	20	90	3.7	0.9/0.95	4000	0.8
2	25	20	85	5.28	0.9/0.95	4000	0.8

S.t. (38) – (43), (53), (54)

$$\min D(P^{DSO}) - \sum_{g=1}^{N_{bus}} \sum_{i=\min(T_{st})}^{\max(T_{end})} \lambda_{g,i} P_{g,i}^{DSO} \quad (59)$$

The coordinated control by IMO is realized by updating the λ . An agreement between EVA and the DSO will be reached if λ converges. In this work, the sub-gradient method [29] is applied to update λ that relies on the multiple iterations of information exchange. The Locational marginal prices for each bus in each iteration can be formulated in the following.

$$\lambda_{g,i}(l+1) = \lambda_{g,i}(l) + \beta(l) \left[\sum_{j=1}^{N_{agg}} (P_j^{ChN*} + P_j^{DisN*}) - P_{g,i}^{DSO*} \right] \quad (60)$$

The convergence condition for the above problem is defined in the following.

$$|\lambda_{g,i}(l+1) - \lambda_{g,i}(l)| \leq \omega \quad (61)$$

In this work, the optimization problem is formulated with YALMIP toolbox under Matlab [30] with the Gurobi solver [31]. In order to solve the problem (53), the Jacobian matrix is derived using MATPOWER [32].

IV. CASE STUDY

In this section, the proposed TE method is applied in a representative distribution system of Denmark to help alleviate congestion and voltage violation problems caused by the simultaneous participation of EVs. The parameters of EVs are presented first. Finally, the results and discussions are given.

A. PARAMETER SETTINGS

In this work, it is assumed that there are two types of EVs managed by two different aggregators in a 10/0.4 kV system which is the same case that is specified in [21]. The power transformer capacity allocated to the EVAs is 70 kW. The minimum/maximum voltage U_{min}/U_{max} per bus is assumed to be 0.9 and 1.1 p.u. respectively. The parameters of each type of EV battery are specified in Table 1.

The historical/predicted prices for each scenario in the DAM are illustrated in Fig. 4. As the driving pattern of each EV owner can be different, the driving behavior of each EV owner is simulated by two aspects: normal daily driving distance considering driving habit, which results in a different initial SOC and minimum required SOC after departure and

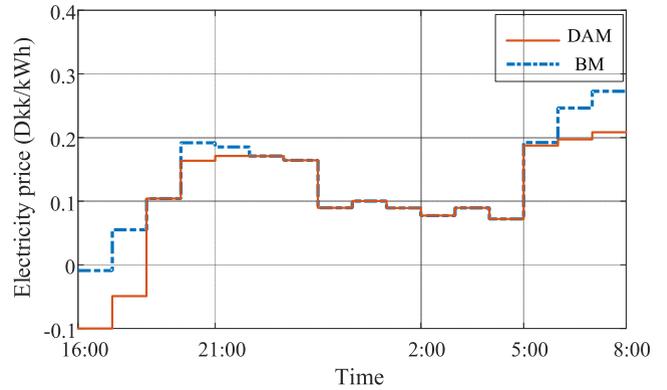


FIGURE 4. Historical electricity markets' price.

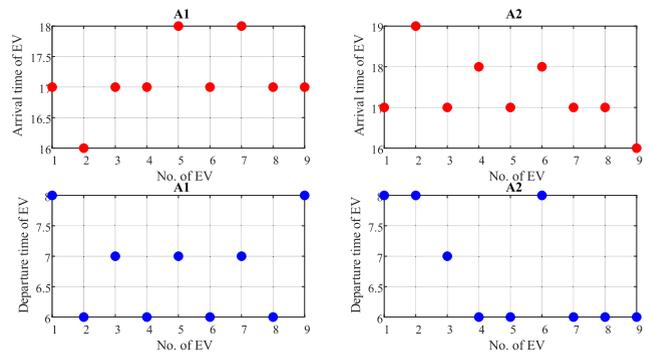


FIGURE 5. Arrival/departure time of each EV of the corresponding aggregator.

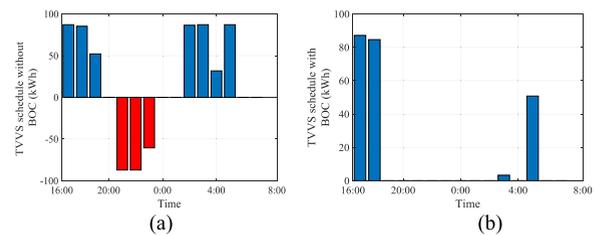


FIGURE 6. Battery optimal schedule. (a) Optimal schedule without considering BOC (Scenario I) (b) Optimal schedule considering BOC (Scenario II).

various arrival and departure times. The arrival/departure time for different EV is illustrated in Fig. 5.

In Fig. 4, the historical DAM and BM price are compared and is considered as the input for the optimization problem specified in section III. B.

B. AGGREGATOR'S OPTIMAL SCHEDULE IN DAM

In this part, the deterministic optimization (DO) with the historical prices is presented. In each scenario, the optimization problem was solved by considering BOC (SI) or not (SII). The schedule for each TVVS is illustrated in Fig. 6.

In Fig. 6, the positive values indicate the charging energy while negative values show the discharging energy. It can be seen that the V2G function will not be used if the BOC is considered.

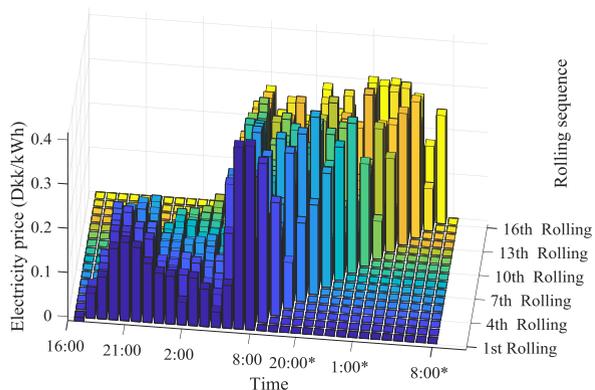
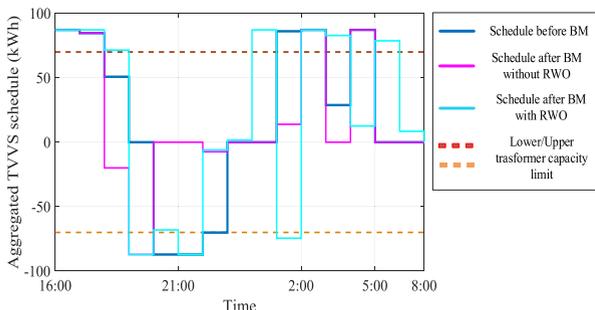
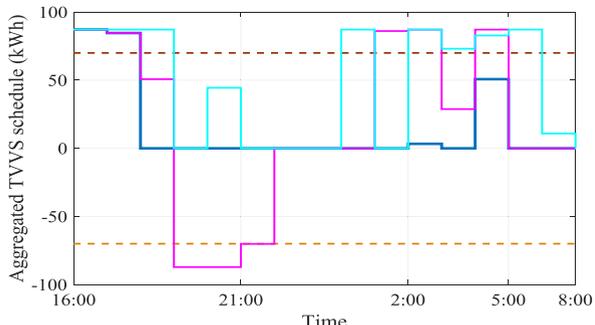


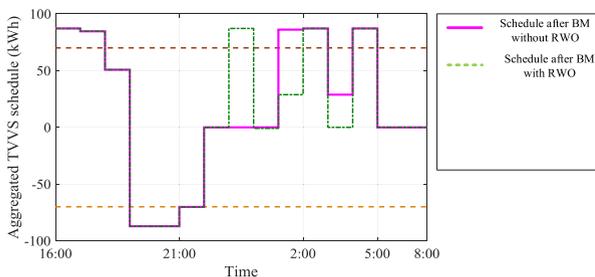
FIGURE 7. The predicted BM price for each rolling process.



(a)



(b)

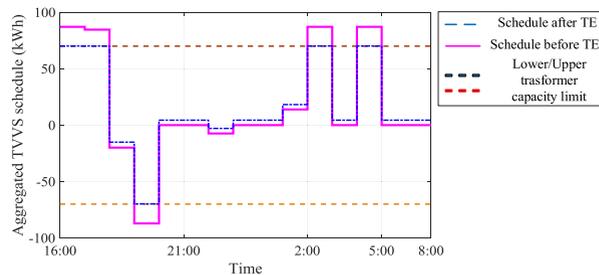


(c)

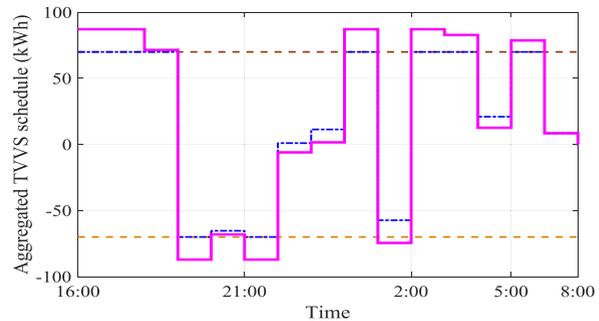
FIGURE 8. The sum of the aggregators' power before and after the BM. (a) Schedule comparison without considering BOC. (b) Schedule comparison considering BOC. (c) Schedule comparison after 1st RWO.

C. AGGREGATOR'S UPDATED SCHEDULE AFTER BM

After bidding in the DAM, the EVAs' schedule can also be updated in the BM. In this work, it is assumed that the prediction error is increased with a maximum step of 1.5% per hour. In other words, the price deviation is increasing

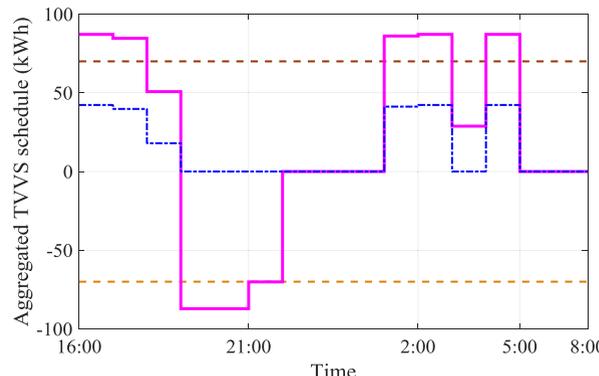


(a)

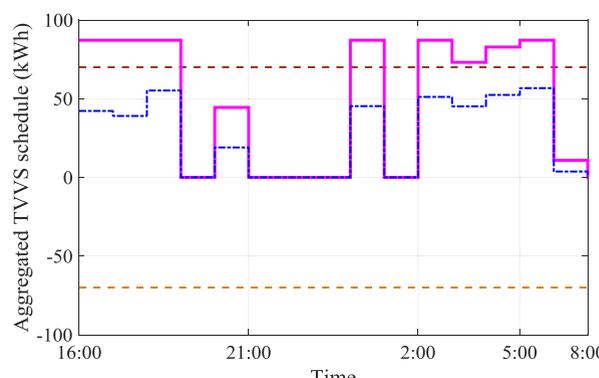


(b)

FIGURE 9. The sum of the aggregators' power before and after the TE without considering BOC. (a) Schedule comparison without RWO. (b) Schedule comparison with RWO.



(a)



(b)

FIGURE 10. The sum of the aggregators' power before and after the TE with considering BOC. (a) Schedule comparison without RWO. (b) Schedule comparison with RWO.

along with the time horizon. The predicted BM price for each rolling procedure is shown in Fig. 7. The optimal schedule

before/ after BM and with/without RWO in the BM are compared in Fig. 8.

It can be seen in Fig. 7 that the price deviation is increasing along with the time horizon. This is according to the fact that the predicted price will be more accurate if the prediction time is closer to the real-time.

After each rolling process, the first time interval schedule will be selected. The final and aggregated schedule before/after BM without using RWO and using RWO is shown as the blue/pink/cyan line segments in Fig. 9 respectively. Comparing Fig. 8 (a) with (b), it can be seen that the congestion problem occurs more frequently when the BOC is considered. Hence, the TE should be applied for resolving the problem.

D. MODIFIED SCHEDULE AFTER APPLYING TE

In this part, the TE is applied for the case with or without considering BOC. If the BOC's impact is neglected, the optimal schedule before and after using TE is shown in Fig. 9. In contrary, the optimal schedule considering BOC's impact is shown in Fig. 10.

The programme was run on a processor of Intel (R) Core (TM) i7-7700HQ CPU @ 2.80 GHz. The computational time of using TE is 119 seconds. As can be seen in both Fig. 9 and 10, the updated schedule via the TE does not incur any congestion problem.

V. CONCLUSION

A continuous operational framework for EVA participation in both the DAM and the BM is proposed. The BOC is considered as an additional operational cost. To meet the system constraints, the TE method is applied to help congestion management and control voltage violations. To reduce the impact of prediction error in electricity price, a RWO method is adopted to get the optimal schedule for EVA. From the simulation, the V2G solution is still too expensive despite recent declines in battery cost. The congestion problem in future distribution system would happen more frequently if EV owners are willing to provide down-regulation service, where network constraints must be taken into account during operation. The proposed framework has advantages in its decentralized structure for implementation and the flexibility in handling the operational interests of different parties.

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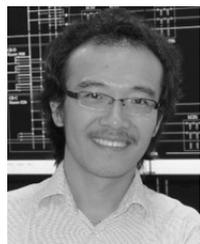
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