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Transactive Real-time Electric Vehicle Charging Management for Commercial Buildings with PV On-site Generation

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***Abstract*—In the future smart grids, it is important for the prosumers to manage the uncertainties from the distributed renewable energy sources (RES) such as PV generation. As a type of distributed energy resources (DERs), electrical vehicles (EVs) are regarded as a promising solution of the problem. In this paper, a transactive real-time EV charging management scheme is proposed for the building energy management system (BEMS) of commercial buildings with PV on-site generation and EV charging services. Instead of direct EV charging control, the proposed EV charging management scheme applies a transactive energy concept based approach to address the real-time EV charging management. With the proposed scheme, the BEMS can schedule its net electricity exchange with the external grid under the uncertainties of PV generation and EV parking and maximize its profit in the real-time operation. Meanwhile, the EV owners need not provide the BEMS with any further private information (such as future driving plans) but only their real-time charging requirements and preference setting of the response to the BEMS's pricing signal in the proposed scheme. As such, the BEMS as a charging service provider only requires the minimal necessary information from the EV owners. The EV owners' charging requirements, preference setting of the response curves and their required reimbursements for the response are respected by the real-time charging management and their contributions to the demand response are reimbursed by the BEMS. Case studies with real world driving data from the Danish National Travel Survey were carried out to verify the proposed framework.**

***Index Terms*—Building energy management system (BEMS), electric vehicles (EVs), photovoltaic (PV), transactive energy.**

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NOMENCLATURE

A. Indices and Sets:

t, τ	Index of time intervals.
$\mathcal{T}$	Set of time intervals for planning.
$\mathcal{H}$	Set of time intervals in prediction horizon of real-time operation.
H	Cardinality of set $\mathcal{H}$.
v	Index of electric vehicles (EVs).
$\mathcal{V}$	Set of EVs actually parked at building in real time.
$\hat{\mathcal{V}}$	Set of EVs estimated to be parked at building in pre-scheduling process.
$\tilde{\mathcal{V}}$	Set of EVs estimated to be parked at building in prediction horizon of real-time operation.
ω	Index of PV output realization scenarios.
Ω	Set of PV output realization scenarios in pre-scheduling process.
$\tilde{\Omega}$	Set of PV output realization scenarios in prediction horizon of real-time operation.

B. Parameters:

B_v	Batter capacity of EV v.
$k_{v,t}$	Response rate of EV v in at time t.
p_t^{pv}	Actual output power of PV panels at time t.
$p_{t,\omega}^{pv}$	Output power of PV panels at time t in scenario ω.
p^{rated}	Rated charging power of charging piles.
$\Delta p_{v,t}^{max}$	Maximum charging power reduction of EV v at time t.
q_t^{con}	Conventional uncontrollable demand at time t.
$s_{v,t}$	EV parking status indicator at time t.
$soc_{v,t}^{max}$	Upper limit of state of charge (SoC) level of the EV battery at time t.
$soc_{v,t}^{min}$	Lower limit of SoC level of EV battery at time t.
α_t^b	Price for buying electricity from microgrid at time t.
α_t^s	Price for selling electricity to microgrid at time t.
β	Penalty coefficient for deviation between scheduled and actual net electricity of BEMS.
γ	Base charging price of EVs.
$\lambda_{v,t}^{max}$	Price requirement for maximum response $\Delta p_{v,t}^{max}$ of EV v at time t.
π_ω	Probability of scenario ω.
Δt	A time interval in the planning.

C. Variables:

$\Delta p_{v,t}^{cl}$ Reduced charging power of EV v based on clearing of transactive market at time t.
$\Delta p_{v,t,\omega}^{cl}$ Reduced charging power of EV v based on clearing of transactive market at time t in scenario ω.
$\widetilde{\Delta p}_{v,\tau,\omega}^{cl}$ Estimated reduced charging power of EV v at time τ in scenario ω in prediction horizon of real-time operation.
$p_{v,t}$ Charging power of EV v at time t.
$p_{v,t,\omega}$ Charging power of EV v at time t in scenario ω.
$\widetilde{p}_{v,\tau,\omega}$ Estimated charging power of EV v at time τ in scenario ω in prediction horizon of real-time operation.
$q_{v,t}$ EV charging energy at time t.
$q_{v,t,\omega}$ Charging energy of EV v at time t in scenario ω.
$\widetilde{q}_{v,\tau,\omega}$ Estimated charging energy of EV v at time τ in scenario ω in prediction horizon of real-time operation.
$soc_{v,t}$ SoC level of EV v at time t.
$soc_{v,t,\omega}$ SoC level of EV v at time t in scenario ω.
$\widetilde{soc}_{v,\tau,\omega}$ Estimated SoC level of EV v at time τ in scenario ω in prediction horizon of real-time operation.
x_t^{pre} Scheduled net electricity exchange between the BEMS and microgrid at time t.
λ_t^{cl} Clearing price of transactive market at time t.
$\lambda_{t,\omega}^{cl}$ Clearing price of transactive market at time t in scenario ω.
$\widetilde{\lambda}_{\tau,\omega}^{cl}$ Estimated clearing price of transactive market at time τ in scenario ω in prediction horizon of real-time operation.
$\Lambda_{v,t}$ Actual charging cost of EV v at time t.
$\Lambda_{v,t}^{cha}$ Cost of charged energy of EV v at time t.
$\Lambda_{v,t}^{res}$ Reimbursement to EV v at time t.

I. Introduction

THERE has been strong growth of distributed energy resources (DERs) at the demand side of the power systems globally in recent years [1], [2]. The increasing number of DERs includes electric vehicle (EV) charging piles and solar photovoltaic (PV) installed in the commercial buildings which are among the most important consumption in the grid. In the United States, commercial buildings account for one third of the total electricity consumption of the country and are projected to grow continuously in the future [3]. The energy management system (EMS) of the commercial buildings will play a more and more important role as a prosumer in the microgrid and future smart grids. With the increasing amount of DERs installed in the commercial buildings, the daily operation of the building energy management system (BEMS) will be subject to the consequential volatility due to the DERs, i.e., the uncertainties of the PV output and EV charging demand.

A number of researches have investigated the optimal EV charging control under the uncertainties of the renewable energy sources (RES). References [4], [5] proposed the charging scheduling of EVs to balance the stochastic wind power for the aggregator and microgrid operator. An online algorithm was proposed in [6] for the load scheduling of the operator of a microgrid with renewable energy, EV and battery storage integration. In [7], a Sortino ratio based portfolio optimization model was proposed to determine the economic dispatch of the microgrid with renewable energy sources and EVs. The study of emission-concerned wind-EV coordination on the transmission grid side was presented in [8]. The aggregator representing a cluster of controllable EVs was coordinated with large-scale wind power in the study. The work in [9] investigated the two-stage framework of the optimal charging for the day-ahead scheduling and real-time operation of an EV charging station with fluctuant renewable energy generation. Reference [10] also proposed a two-stage optimal framework for the economic operation of an EV parking lot to deal with the uncertainty of solar energy. A two-stage framework with a normalized Nash equilibrium approach was also proposed for the day-ahead scheduling and real-time operation of the EV aggregator at the residential transformer level in [11]. The objective is to manage the congestion constraint and renewable energy utility uncertainty. The work in [12] scheduled the charging of the employee EVs in the office buildings optimally to cope with the power consumption and PV output. An operation strategy for the building microgrid containing EVs and PV was proposed in [13] to improve the self-consumption of the PV energy. Besides, the optimal coordinated control of EV charging was also researched in a number of studies to provide ancillary services and satisfy the network constraints [14]–[19].

The aforementioned studies have provided valuable insights of the optimal EV charging scheduling under the uncertainty of renewable energy generation. However, their focuses lie in the operation of the residential aggregators and microgrid operators. As the EV charging controllers, the aggregators and system operators have the full permission of the charging control in the existing literature. The cost of the aggregators and system operators to employ the charging flexibility of the EV owners is not considered in the models. The EV owners need to notify the aggregators and system operators of the driving/parking activity details for the charging management. In the real-world cases of the commercial building parking lots, such schemes sometimes may not be practical. The EV owners are not the long-term customers of the BEMS of the commercial buildings. Full control permission of the EV charging is not always available to the system operator any more. Meanwhile, the EV owners have different acceptance levels for the system operator to modify their charging schedules. They allow the system operator to change their charging demand to varying extents. Consequently, the necessary reimbursement for their provided flexibility are different. Further, the EV owners may be unwilling (and sometimes unable) to provide the detailed parking/driving plans to the BEMS in the cases of commercial buildings. Therefore, a novel real-time EV charging control method is proposed in this paper for the BEMS of a commercial building to meet these challenges. In this paper, a transactive energy concept based real-time EV charging management scheme is designed for the BEMS of a commercial building to track the fluctuant PV on-site generation. The transactive control can fully utillizes the response potential of the control targets without raising privacy

issues, and has been tested in a few pilot projects for building and residential energy management [20]. Thus, it is employed in the proposed method for the energy management of BEMS. The contributions of the work in this paper are summarized as follows. A transactive EV charging management scheme is proposed for the real-time operation of the BEMS of commercial buildings with PV on-site generation and EV charging services. With the proposed scheme, the BEMS can handle the uncertainties of PV generation and EV parking optimally when scheduling its net electricity exchange with the external grid. Meanwhile, only minimum necessary information from the EV owners is required by the proposed scheme. More importantly, the charging requirements, preference setting of the response curves and the required reimbursements for the response of the EV owners are respected by the real-time operation of the BEMS. Further, an elitist GA based heuristic algorithm is proposed for the BEMS to determine the pre-scheduling and real-time operation decisions in the transactive control scheme.

The paper is organized as follows. The control framework of the BEMS of a commercial building with EV charging services and PV on-site generation is introduced in Section II. The transactive EV charging management method for the BEMS to handle the real-time operation is presented in detail. The stochastic programming models of the BEMS to determine the scheduled operation points and real-time EV charging decisions are described in Section III. In Section IV, the results of the case studies are presented and discussed. Finally, the conclusions are presented in Section V.

II. Energy Management Framework for Commercial Buildings with EVs and PV

In this paper, the BEMS of the commercial building with EV charging infrastructures and PV on-site generation is considered as a prosumer in a microgrid context [21]. The system control framework is shown in Fig. 1. The microgrid operator (MGO) acts as the leader of the system operation and determine the dynamic system prices for the demand and supply in the microgrid. The BEMS of the commercial building, which is one of the prosumers in the microgrid, is a follower in the system operation and react to the MGO's decisions. Before the real-time operation, the MGO determines the dynamic system prices and broadcasts them to all the prosumers in the microgrid. The prosumers determine their energy schedules according to the system prices and send their schedules to the MGO. With the scheduled net electricity of all the prosumers in the microgrid, the MGO participates in the wholesale market to import/export electricity from/to the utility grid. During the real-time operation, the prosumers implement their own control strategies and the actual net electricity is determined accordingly. The settlement between the MGO and prosumers is determined by the actual net electricity of the prosumers in real time. However, the prosumers will be penalized for the deviation between their scheduled and actual net electricity by the MGO. Thus, there is a strong motivation for the prosumers to tract their pre-scheduled energy plans. In this paper, the BEMS of the commercial building employs the flexibility of the EV charging to achieve this goal under the uncertainties of the PV output and EV parking.

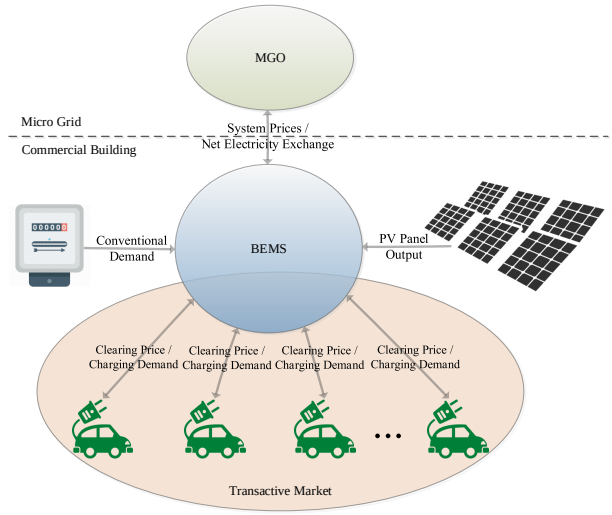


Fig. 1. System Framework of BEMS with EVs and PV in Microgrid.

In order to employ the EV charging flexibility in the real-time operation, the BEMS organizes a transactive market with the EVs parked in the building parking lot. The mechanism of the transactive market is as follows. In every time interval, the owners of the EVs parked in the commercial building can submit their charging limits and response curves of the charging to the BEMS to join the transactive market and offer their charging flexibility. As a result, they will get reimbursed for the flexibility they offer to the BEMS. The response curve of the EV charging is illustrated in Fig. 2.

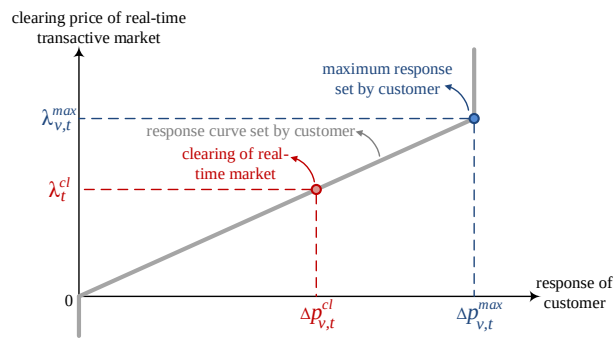


Fig. 2. Illustration of the EV Response Curves in the Transactive Market.

Without any incentives, the EV owners will charge their EVs at the rated charging power with the base charging price till the target state-of-charge (SoC) levels. By joining the transactive market, the EV owners allow the BEMS to reduce their charging power of the EVs in the interval according to their response curves for the reimbursement from the BEMS. Thus, the actual charging power in the interval is the rated power of the EV charging p^{rated} minus the reduced power $\Delta p_{v,t}^{cl}$ as (1).

$$q_{v,t} = \left(p^{rated} - \Delta p_{v,t}^{cl}\right) \Delta t \tag{1}$$

In each time interval, each EV owner submits his/her response rate and maximum response limit to the BEMS. As such, his/her response curve as shown in Fig. 2 in the

transactive market is determined. Then, the BEMS clears the transactive market at the clearing price λ_t^{cl} for the interval and broadcasts the price to all the EV owners. The clearing price λ_t^{cl} is obtained by the BEMS's own optimization. The responses of the EV owners are determined according to the response curves and clearing price as shown in Fig. 2. The mathematical formulation is as (2). The coefficient $k_{v,t}$ in (2) is the inverse of the response curve's slope, which is a customer-setting parameter. The larger $k_{v,t}$ is, more power of the EV charging will be reduced in the interval with the same clearing price, which means the EV owner is more willing to offer charging flexibility to the BEMS.

$$\Delta p_{v,t}^{cl} = \begin{cases} k_{v,t}\lambda_t^{cl} & (\lambda_t^{cl} \leqslant \lambda_{v,t}^{max}) \\ \Delta p_{v,t}^{max} & (\lambda_t^{cl} > \lambda_{v,t}^{max}) \end{cases} \tag{2}$$

When the clearing price of the transactive market and reduced charging power of the EVs are determined, both the cost for the charged energy of the EVs and reimbursement for their response can be calculated accordingly. The cost of the charged energy $\Lambda_{v,t}^{cha}$ is equal to the charged electricity multiplied by the base charging price γ. The reimbursement to the EVs for their response $\Lambda_{v,t}^{res}$ is proportional to the EVs' reduced charging power and clearing price of the transactive market λ_t^{cl} in the interval. As such, the actual charging cost of the EVs in the interval $\Lambda_{v,t}$ is equal to the charged energy cost $\Lambda_{v,t}^{cha}$ minus the reimbursement $\Lambda_{v,t}^{res}$, and can be calculated as (3). The reimbursement reduces the actual payment for the charging of the EVs and it is calculated based on the amount of the reduced power of the EV's own charging. Thus, the EV owners are encouraged to provide as much flexibility as possible by the proposed transactive scheme while their own preferences are respected by the final solution.

$$\Lambda_{v,t} = \Lambda_{v,t}^{cha} - \Lambda_{v,t}^{res} = \gamma q_{v,t} - \lambda_t^{cl}\Delta p_{v,t}^{cl}\Delta t \tag{3}$$

III. Formulation of Pre-scheduled Energy Plan and Real-time Operation for BEMS

A. Pre-scheduled Energy Plan Model of BEMS

Before the real-time operation, the BEMS schedules its net electricity and send the scheduled energy plan to the MGO. The objective of the pre-scheduled energy plan of the BEMS is to maximize its expected profit in the real-time operation. It is expressed as the stochastic programming problem below.

$$\begin{aligned} \max_{x_t^{pre}} \sum_{\omega\in\Omega} \pi_\omega \Bigg[& \sum_{t\in\mathcal{T}}\sum_{v\in\widehat{\mathcal{V}}} \left(\gamma p_{v,t,\omega} - \lambda_{t,\omega}^{cl}\Delta p_{v,t,\omega}^{cl}\right)\Delta t \\ & - \sum_{t\in\mathcal{T}} \alpha_t^b \left[\sum_{v\in\widehat{\mathcal{V}}} p_{v,t,\omega}\Delta t + q_t^{con} - p_{t,\omega}^{pv}\Delta t,\ 0\right] \\ & - \sum_{t\in\mathcal{T}} \alpha_t^s \left[\sum_{v\in\widehat{\mathcal{V}}} p_{v,t,\omega}\Delta t + q_t^{con} - p_{t,\omega}^{pv}\Delta t,\ 0\right] \\ & - \beta \sum_{t\in\mathcal{T}} \left| x_t^{pre} + p_{t,\omega}^{pv}\Delta t - q_t^{con} - \sum_{v\in\widehat{\mathcal{V}}} p_{v,t,\omega}\Delta t \right| \Bigg] \end{aligned} \tag{4}$$

Subject to

$$soc_{v,t}^{min} \leqslant soc_{v,t,\omega} \leqslant soc_{v,t}^{max} \quad \forall t\in\mathcal{T} \quad \forall v\in\widehat{\mathcal{V}} \quad \forall\omega\in\Omega \tag{5}$$

$$soc_{v,t,\omega} = q_{v,t,\omega}/B_v + soc_{v,t-1,\omega} \quad \forall t\in\mathcal{T} \quad \forall v\in\widehat{\mathcal{V}} \quad \forall\omega\in\Omega \tag{6}$$

$$q_{v,t,\omega} = \left(p^{rated} - \Delta p_{v,t,\omega}^{cl}\right) s_{v,t}\Delta t \quad \forall t\in\mathcal{T} \quad \forall v\in\widehat{\mathcal{V}} \quad \forall\omega\in\Omega \tag{7}$$

$$\Delta p_{v,t,\omega}^{cl} = \left\lfloor k_{v,t}\lambda_{t,\omega}^{cl},\ \Delta p_{v,t}^{max} \right\rfloor \quad \forall t\in\mathcal{T} \quad \forall v\in\widehat{\mathcal{V}} \quad \forall\omega\in\Omega \tag{8}$$

$$q_{v,t,\omega} \geqslant 0 \quad \forall t\in\mathcal{T} \quad \forall v\in\widehat{\mathcal{V}} \quad \forall\omega\in\Omega \tag{9}$$

where x_t^{pre} is the scheduled net electricity exchange between the BEMS and microgrid at time t; $p_{v,t,\omega}$ is the charging power of EV v at time t in scenario ω; $q_{v,t,\omega}$ is the charged electricity of EV v at time t in scenario ω, and $q_{v,t,\omega} = p_{v,t,\omega}\Delta t$. The objective of the stochastic programming problem (4) aims to maximize the expected profit of the BEMS. It consists of four terms. The first term is the revenue from the EV charging. It equals to the base charging cost minus the reimbursement to the EV owner in the transactive market. The second and third terms are the settlement for electricity exchange between the BEMS and MGO. It is determined by the system prices determined by the MGO and the actual net electricity of the commercial building. The second term is the payment of the BEMS to import electricity from the microgrid, and the third term is the revenue of the BEMS to export electricity to the microgrid. Generally, the internal buying price α_t^b is higher than the internal selling price α_t^s. The fourth term is the penalty to the BEMS for the deviation between the scheduled and actual net electricity of the commercial building. It is to be noted that the revenue from electricity consumption of the conventional uncontrollable demand is constant and neglected in the optimization. Meanwhile, the optimization problem is subject to the EV charging constraints as (5)-(9). For the SoC limit constraint (5), the SoC levels of the EV batteries are within the specified range with the expected charging plan. The EV SoC levels of each time interval during parking of the batteries are determined by the charged electricity (6). The charged electricity of the parked EVs are determined by the actual charging power as (7) and (8). The parameter $s_{v,t}$ in (7) is the parking status indicator of the EVs. It is equal to 1 when the EV is parked in the commercial building and available for charging, and is equal to 0 when the EV is not parked in the building. As vehicle-to-grid (V2G) technology is not considered in this paper, the EV charging energy is constrained positive as (9).

In the pre-scheduling optimization of the BEMS, the PV outputs $p_{t,\omega}^{pv}$ are stochastic parameters dependent on the scenario ω. Meanwhile, the EV parking status $s_{v,t}$ and initial SoC levels of the EVs soc_{v,t_0} are uncertain and will be different in the actual case in real time. In the result of the pre-scheduling optimization, only the net-energy exchange x_t^{pre} will be applied and submitted to the MGO. The solutions in the scenarios of the pre-scheduling optimization including

$\Delta p_{v,t,\omega}^{cl}$, $p_{v,t,\omega}$, $q_{v,t,\omega}$ and $\lambda_{t,\omega}^{cl}$ will not be applied in the actual control of the BEMS. In the real-time operation, when the aforementioned uncertain parameters are determined, the BEMS will carry out the real-time operation optimization to determine these control variables as presented in the following subsection.

B. Real-time EV Charging Operation of BEMS

Before the real-time operation, the BEMS schedules the net electricity exchange with the microgrid according to the forecast of the PV output and the expected set of EV parking activities. In the real-time operation, the BEMS need to determine the actual control strategies of the EV charging with the new information available to the BEMS in every time interval. Due to its inherent uncertainty, the output of the PV panels may be different from the expected values of the forecast probability space in the pre-scheduling optimization. Meanwhile, the arrival number, departure number and demand to be charged of the EVs in the commercial building parking lot in real time may also be different from the expected set used in the pre-scheduling optimization of the BEMS. Thus, the net electricity exchange of the commercial building with the microgrid will deviate from the pre-scheduled plan if there is no proper control measurement from the BEMS and result in a high penalty by the MGO. In order to tract the scheduled net electricity plan and maximize its own profit, the BEMS organizes a real-time transactive market with the EV owners to recruit the charging flexibility from the EVs. The real-time charging management process with the transactive market between the BEMS and EV owners is as described in Section II. In the real-time operation, the arrival and departure of the EVs in the current interval are certain. The EVs parked in the parking lot of the commercial building send the charging requests and response curves to the BEMS. The BEMS clears the market according to the available information in real time and broadcasts the clearing price of the current interval to the EVs in the parking lot. With the clearing price of the transactive market, the charging control decisions of the EVs are obtained according to (1) to (3).

In the real-time operation, the actual charging control strategies of the EVs are determined by the clearing of the transactive market between the BEMS and EV owners. It is critical for the BEMS to clear the transactive market optimally. Model predictive control (MPC) is a widely accepted modern control strategy which can effectively deal with system uncertainties [22]. Thus, a rolling-horizon optimization based on MPC is proposed for the BEMS to obtain the clearing prices in the real-time operation. The details of the proposed real-time optimization of the BEMS are described as follows. In each time interval, the BEMS carries out the real-time optimization which maximizes its surplus of the current interval t and expected surplus of the following intervals in the prediction horizon $\mathcal{H} = \{t+1, t+2, \cdots t+H\}$. However, only the clearing price of the current interval from the solution of the optimization will be actually implemented by the BEMS to clear the transactive market. The solution for the following intervals will be kept on hold. In the following interval, the BEMS updates the available information and forecast, carries out the optimization again and implements the decisions of the following interval. The BEMS keeps performing the process to clear the transactive market and obtain the real-time charging control strategies for the EVs. The real-time optimization of the BEMS is formulated as (10)-(20).

$$\begin{aligned}
&\max_{\lambda_t^{cl}, \widetilde{\lambda}_{\tau,\omega}^{cl}} \sum_{v\in\mathcal{V}} \left(\gamma p_{v,t} - \lambda_t^{cl}\Delta p_{v,t}^{cl}\right)\Delta t \\
&- \alpha_t^b \left[\sum_{v\in\mathcal{V}} p_{v,t}\Delta t + q_t^{con} - p_t^{pv}\Delta t,\, 0\right] \\
&- \alpha_t^s \left[\sum_{v\in\mathcal{V}} p_{v,t}\Delta t + q_t^{con} - p_t^{pv}\Delta t,\, 0\right] \\
&- \beta \left| x_t^{pre} + p_t^{pv}\Delta t - q_t^{con} - \sum_{v\in\mathcal{V}} p_{v,t}\Delta t \right| \\
&+ \sum_{\omega\in\widetilde{\Omega}} \pi_\omega \left[\sum_{\tau\in\mathcal{H}}\sum_{v\in\widetilde{\mathcal{V}}} \left(\gamma \widetilde{p}_{v,\tau,\omega} - \widetilde{\lambda}_{\tau,\omega}^{cl}\widetilde{\Delta p}_{v,\tau,\omega}^{cl}\right)\Delta t \right. \\
&- \sum_{\tau\in\mathcal{H}} \alpha_\tau^b \left[\sum_{v\in\widetilde{\mathcal{V}}} \widetilde{p}_{v,\tau,\omega}\Delta t + q_\tau^{con} - p_{\tau,\omega}^{pv}\Delta t,\, 0\right] \\
&- \sum_{\tau\in\mathcal{H}} \alpha_\tau^s \left[\sum_{v\in\widetilde{\mathcal{V}}} \widetilde{p}_{v,\tau,\omega}\Delta t + q_\tau^{con} - p_{\tau,\omega}^{pv}\Delta t,\, 0\right] \\
&\left. - \beta \sum_{\tau\in\mathcal{H}} \left| x_\tau^{pre} + p_{\tau,\omega}^{pv}\Delta t - q_\tau^{con} - \sum_{v\in\widetilde{\mathcal{V}}} \widetilde{p}_{v,\tau,\omega}\Delta t \right| \right]
\end{aligned} \tag{10}$$

Subject to

$$soc_{v,t}^{min} \leqslant soc_{v,t} \leqslant soc_{v,t}^{max} \quad \forall v \in \mathcal{V} \tag{11}$$

$$soc_{v,t} = q_{v,t}/B_v + soc_{v,t-1} \quad \forall v \in \mathcal{V} \tag{12}$$

$$q_{v,t} = \left(p^{rated} - \Delta p_{v,t}^{cl}\right)\Delta t \quad \forall v \in \mathcal{V} \tag{13}$$

$$\Delta p_{v,t}^{cl} = \left\lfloor k_{v,t}\lambda_t^{cl}, \Delta p_{v,t}^{max} \right\rfloor \quad \forall v \in \mathcal{V} \tag{14}$$

$$q_{v,t} \geqslant 0 \quad \forall v \in \mathcal{V} \tag{15}$$

$$\begin{aligned} soc_{v,\tau}^{min} \leqslant \widetilde{soc}_{v,\tau,\omega} \leqslant soc_{v,\tau}^{max} \quad \forall \tau \in \mathcal{H} \\ \forall v \in \widetilde{\mathcal{V}} \quad \forall \omega \in \widetilde{\Omega} \end{aligned} \tag{16}$$

$$\begin{aligned} \widetilde{soc}_{v,\tau,\omega} = \widetilde{q}_{v,\tau,\omega}/B_v + \widetilde{soc}_{v,\tau-1,\omega} \quad \forall \tau \in \mathcal{H} \\ \forall v \in \widetilde{\mathcal{V}} \quad \forall \omega \in \widetilde{\Omega} \end{aligned} \tag{17}$$

$$\begin{aligned} \widetilde{q}_{v,\tau,\omega} = \left(p^{rated} - \widetilde{\Delta p}_{v,\tau,\omega}^{cl}\right) s_{v,\tau}\Delta t \quad \forall \tau \in \mathcal{H} \\ \forall v \in \widetilde{\mathcal{V}} \quad \forall \omega \in \widetilde{\Omega} \end{aligned} \tag{18}$$

$$\begin{aligned} \widetilde{\Delta p}_{v,\tau,\omega}^{cl} = \left\lfloor k_{v,\tau}\widetilde{\lambda}_{\tau,\omega}^{cl}, \Delta p_{v,\tau}^{max} \right\rfloor \quad \forall \tau \in \mathcal{H} \\ \forall v \in \widetilde{\mathcal{V}} \quad \forall \omega \in \widetilde{\Omega} \end{aligned} \tag{19}$$

$$\widetilde{q}_{v,\tau,\omega} \geqslant 0 \quad \forall \tau \in \mathcal{H} \quad \forall v \in \widetilde{\mathcal{V}} \quad \forall \omega \in \widetilde{\Omega} \tag{20}$$

The objective of the BEMS's real-time optimization (10) consists of two parts: the surplus of the BEMS in the current interval and expected surplus in the prediction horizon of the

MPC based approach. The first four terms in (10) make up of the surplus of the BEMS in the current interval. The first term is the revenue of the charging from the EV owners. It equals to the base charging fee minus the reimbursement to the EV owners for their flexibility. The second term is the payment to import electricity from the microgrid, and the third term is the surplus to export electricity to the microgrid. The fourth term is the penalty for the deviation of the actual net electricity from the pre-determined schedule of the BEMS. The last four terms of (10) make up of the expected surplus of the BEMS in the following intervals of the prediction horizon $\mathcal{H}$. The fifth term of (10) is the expected revenue of the charging from the EV owners in $\mathcal{H}$. The sixth and seventh terms of (10) are the expected payment/surplus of the BEMS to import/export electricity from/to the microgrid in $\mathcal{H}$, respectively. The last term of (10) is the expected penalty for the deviation of the BEMS's net electricity from its pre-determined schedule in $\mathcal{H}$. In the decision variables of the BEMS's real-time optimization, $\widetilde{\lambda}^{cl}_{\tau,\omega}$ is the estimated clearing price of the transactive market in time interval τ in the prediction horizon of scenario ω. However, the BEMS will not use it directly to clear the transactive market at time τ but updated it in the optimization of the following intervals when the new information is available to BEMS. Only the clearing price of the current interval λ^{cl}_t will be implemented by the BEMS to clear the transactive market in the current interval, and the charging control decisions of the EVs in the current interval $p_{v,t}$ are determined accordingly.

The real-time optimization of the BEMS is subject to the EV charging and response constraints of the current interval and following intervals in the prediction horizon $\mathcal{H}$ as (11)-(20). Constraints (11)-(15) are the constraints for the current interval. The SoC levels of the EV batteries are constrained within the specified range with the expected charging plan as (11). The EV SoC levels are calculated with the charged electricity in the interval as (12). The charged electricity of the parked EVs are determined by the actual charging power as (13) and (14). The EV charging energy flow is constrained unidirectional as (15). For the EV charging of the intervals in the prediction horizon $\mathcal{H}$, the estimated charging strategies meet the charging requirements and response curves of the EV owners with constraints (16)-(20). In each time interval, the BEMS updates the real-time information including the arrival and departure of the EVs, the charging requests and response curves of the EV owners, the output of the PV panels and the forecast in the prediction horizon and conducts the optimization problem (10) subject to the constraints (11)-(20). The BEMS clears the real-time transactive market with λ^{cl}_t according to the result of the optimization.

Both optimization models for the pre-scheduling and real-time control are non-linear, non-convex optimization problems and NP-hard to solve. Heuristic algorithms are commonly used to solve such problems. In this study, an elitist genetic algorithm is used to solve the optimization problems for its good performance with the current parallel computing technology [23]–[25]. The flow diagram of the proposed EV charging management for the BEMS is shown in Fig. 3.

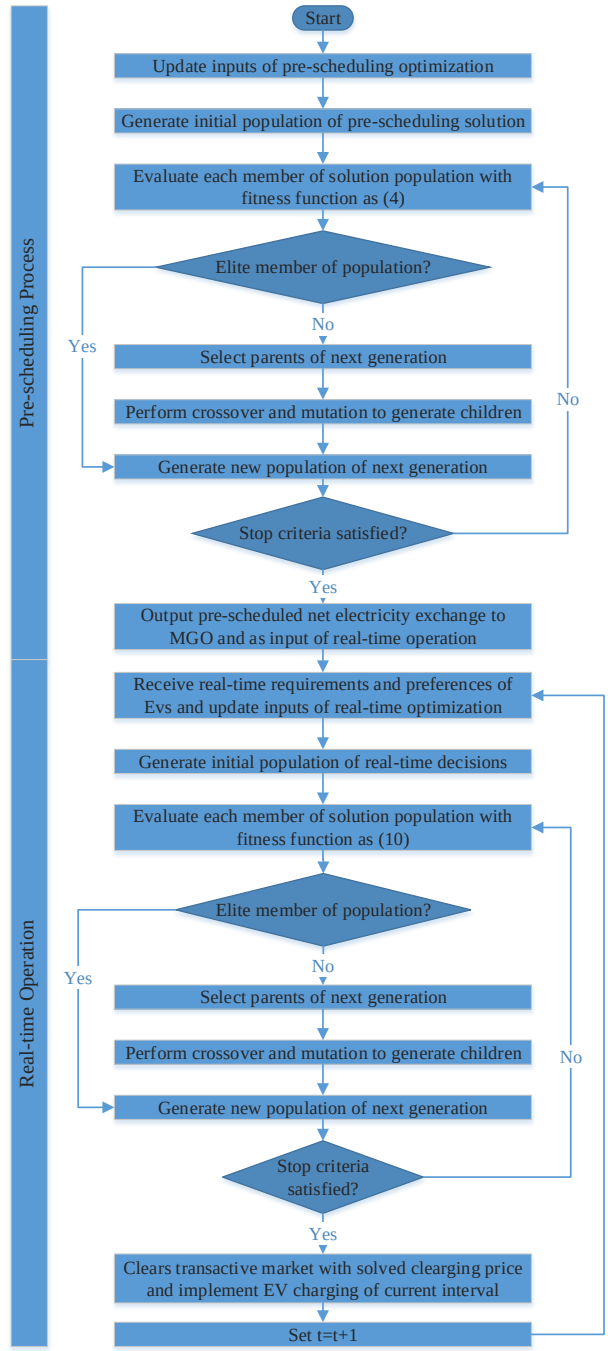


Fig. 3. Flow Diagram of Proposed Transactive EV Charging Management for BEMS.

IV. Case Studies

Case studies were carried out to validate the proposed real-time EV charging management for the BEMS of the commercial building with PV on-site generation.

A. Parameters in the Case Studies

In the simulation, the case of an commercial building with PV on-site generation and EV charging services was studied. The parking lot in the studied commercial building has 250 parking places equipped with charging infrastructures. The

parking activities of the EVs in the case study were simulated with the real world data from the Danish National Travel Surveys [26]. In the case study, the actual parking activities of the EVs in real time are assumed to deviate from the expected EV parking activities of the parking lot. The expected and actual arrival/departure EV numbers of the parking lot are shown in Fig. 4. The deviation of the parked EV numbers between the expectation and actual case is shown in Fig. 5. The key parameters of the EVs and charging in the case study are listed in Table I.

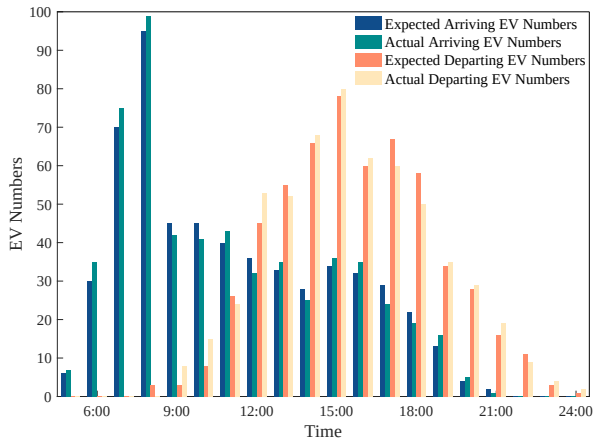


Fig. 4. Expected Arrival and Departure EV Numbers in Case Study.

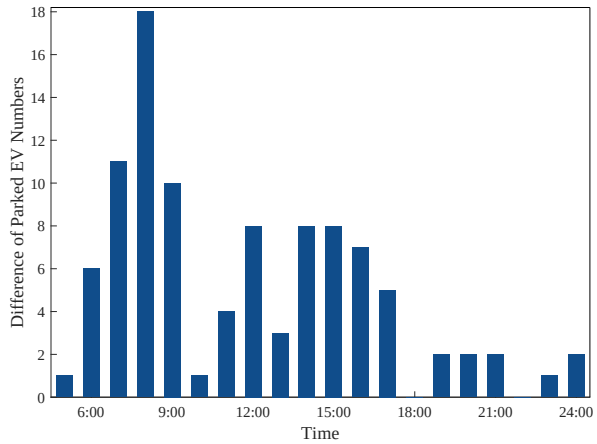


Fig. 5. Deviation between Expectation and Actual Parked EV Numbers in Case Study.

TABLE I
KEY PARAMETERS OF EVS

Parameter	Value
EV Battery Capacity	60kWh
Energy Consumption Rate	150Wh/km
Lower/Upper SoC Level Limit	20% / 85%
Charging Power Limit	10kW

The base electricity price for the EV charging is set to be 0.8 DKK/kWh. The internal buying and selling electricity prices of the microgrid in the case study are shown in Fig. 6. In the case study, the penalty coefficient for the net electricity exchange deviation with the microgrid is set to be 0.3 DKK/kWh.

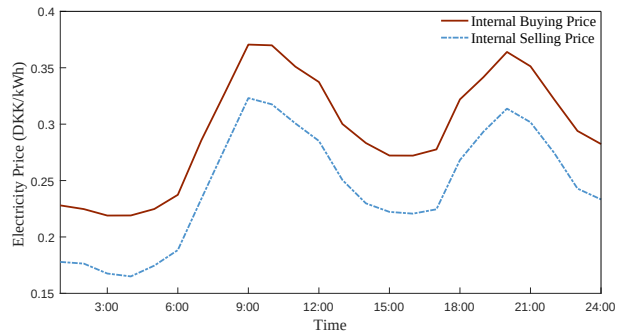


Fig. 6. Internal Electricity Prices of Microgrid in Case Study.

The solar output in the case study is shown in Fig. 7. The actual output levels of the PV panels fluctuate around the expected values of the forecast probability space in the pre-scheduling process in the case study. Typically, a time-shifting on the predicted peak output of the PV panels in the morning is also simulated and analyzed in the case.

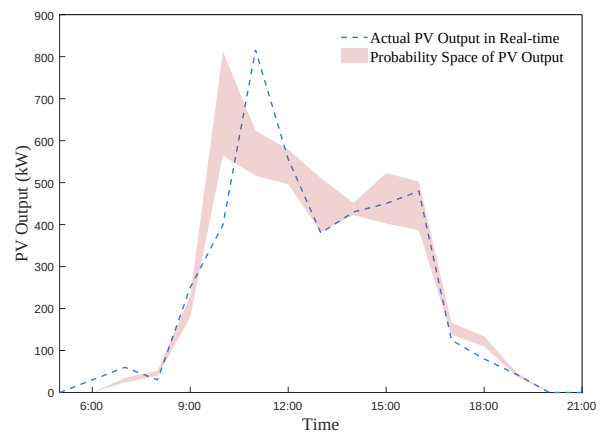


Fig. 7. Output of PV Panels in Case Study.

The optimization problems in the case study were solved on a laptop with Intel Core i5 CPU (2.30GHz) and 8GB RAM. The mean running time of the optimization for each real-time EV charging operation of the BEMS is about 66 seconds. The real-time operation of the BEMS is scheduled on an hourly basis. Thus, the running time of the proposed algorithm can meet the time requirement of the scheduling problem.

B. Case Study Results

Before the real-time operation, the BEMS pre-schedules the net electricity exchange with the microgrid. The BEMS carries out the pre-scheduling optimization to determine the pre-scheduled net electricity exchange and submits this pre-scheduling energy plan to the MGO. The pre-scheduled net electricity exchange is obtained by the optimal arguments x_t^{pre} of the pre-scheduling optimization of the BEMS. The pre-scheduled net electricity exchange of the BEMS with the microgrid is shown in Fig. 8. Positive amount in the figure means the BEMS imports electricity from the microgrid while negative amount means the BEMS exports electricity to the microgrid.

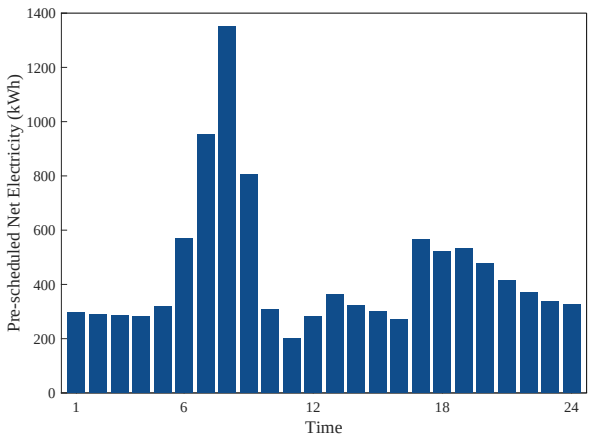


Fig. 8. Pre-scheduled Net Electricity Exchange of BEMS.

In the real-time operation of the proposed charging management approach, the BEMS clears the proposed transactive market and determines the actual charging decisions of the EVs. Fig. 9 shows the actual EV charging demand in real time without the proposed charging management (Case 1), the EV charging demand with the proposed transactive charging management (Case 2) and the optimal solution of the EV charging demand with perfect information (Case 3). For the optimal solution, it is assumed that all the information including the arrival and departure of all the EVs, the output levels of the PV panels throughout the planning horizon are known to the BEMS in advance. As shown in the figure, the EV charging demand with the proposed transactive charging management is similar to the optimal solution with perfect information. The charging demand at 7 am, 8 am, 10 am and 1 pm is delayed to 9 am, 11 am, 12 pm and 2 pm by both the proposed charging management and optimal solution in order to limit the deviation of the net electricity exchange of the BEMS with the microgrid from the pre-scheduled net electricity exchange. The proposed transactive EV charging management approach is able to provide the charging decisions which are close enough to the global optimal solution.

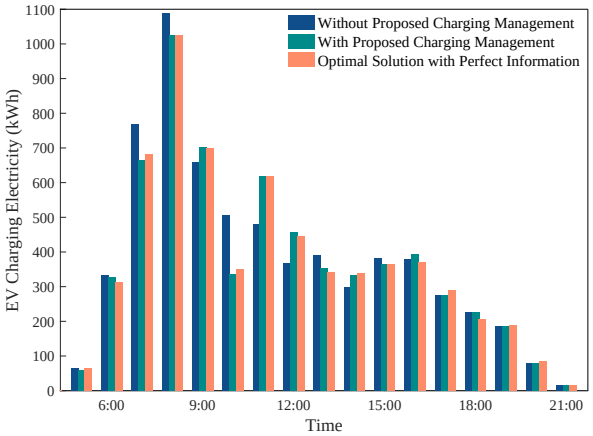


Fig. 9. Real-time EV Charging Demand of BEMS.

The deviation of the actual net electricity exchange of the BEMS with the microgrid in the real time operation from the pre-scheduled plan is shown in Fig. 10. Due to the uncertainties of the PV and EVs, the net electricity exchange of the BEMS with the microgrid strongly deviates from the pre-scheduled plan between 6 am and 3 pm without the proposed EV charging management. Specifically, more electricity is consumed than the pre-scheduled plan in 7 am and 8 am mainly because of the unexpected extra arrival of EVs in the parking lot. The forecast error of the PV output in the pre-scheduling optimization is the main reason of the great deviations of the net electricity from 10 am to 3 pm. Nevertheless, the EV charging demand with the proposed transactive charging management is able to alleviate the net electricity exchange deviation by the real-time operation of the BEMS. The real-time EV charging demand is scheduled and shifted by the BEMS as shown in Fig. 9 to cope with the uncertainties of the EV parking and the errors of the actual PV generation from the forecast.

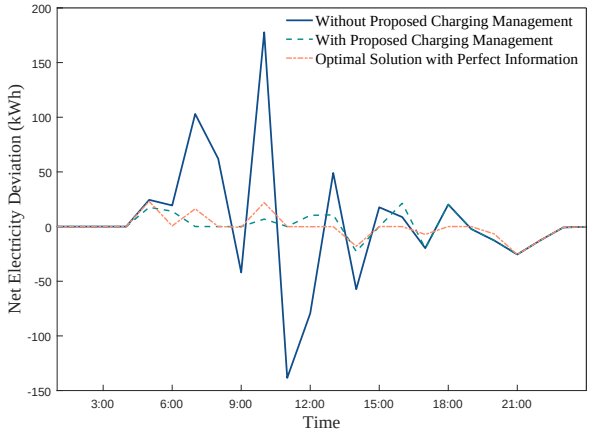


Fig. 10. Net Electricity Exchange Deviation of BEMS in Real Time.

The balance of the BEMS in the three different cases is shown in Table II. The payment of the BEMS for importing electricity from the microgrid and income for the EV charging from the EV owners are similar in the three different cases. However, the penalty for the deviation of the real-time net electricity exchange from the pre-scheduled plan of the BEMS by the MGO is much higher without the proposed real-time EV charging management method due to the uncertainties of the PV generation and EV parking events. The high penalty from the MGO results in a lower total surplus of the BEMS. In contrast, the deviation of the real-time net electricity exchange from the pre-scheduled net electricity exchange of the BEMS is limited by the proposed method. Therefore, the penalty of the BEMS by the MGO drops significantly. It is shown that the penalty from the MGO decreases from about 262 DKK without the real-time charging management to about 59 DKK with the proposed real-time operation, which is a 77% drop. Both the reimbursement to the EV owners and penalty from the MGO with the proposed EV charging management framework are just slightly higher than the optimal solution with perfect information, and the total surplus of the BEMS in the two cases is almost the same. Thus, the proposed transactive EV charging management framework for BEMS is able to maximize the BEMS's surplus under the uncertainties.

TABLE II
BALANCE OF BEMS IN REAL TIME OPERATION

Unit: DKK	**Case 1**	**Case 2**	**Case 3**
Payment for importing electricity	-3274.9	-3250.4	-3247.2
Revenue for exporting electricity	0	0	0
Charging fee from EVs	5202.0	5132.5	5121.1
Reimbursement for response to EVs	0	-33.6	-29.3
Penalty by MGO	-262.0	-59.4	-40.2
Total	1665.1	1789.2	1804.4

In the simulation, all the real-time EV charging decisions with the proposed method meet the charging requirements of the EV owners. No violation on the charging requirements of the EVs happened in the simulation because the final decision of the EV charging strategy is based on the EV owners' own preferences with the clearing price of the real-time transactive market. The EV owners' requirements and preferences are always respected by the BEMS with the proposed method.

In order to illustrate the reliability of the proposed heuristic algorithm, the case with the proposed energy management approach in the case study was simulated repeatedly for 50 times. The solutions show great consistency. The balance of the BEMS in the repetitive simulations is shown in Fig. 11. The standard deviation of the solutions in the repetitive simulations is less than 4 DKK. As shown in the figure, the solutions are close enough to the optimal solution. The elitist GA based heuristic algorithm performs consistently with the proposed framework.

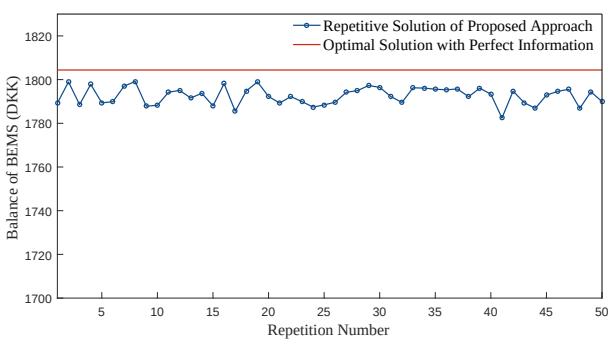


Fig. 11. Balance of BEMS in Repetitive Simulations of Case Study.

C. Comparison with Direct Control

In the existing studies, the EV charging control was widely performed by direct control of the fleet operator [27], [28]. The EV owners notify the fleet operator of the arrival and departure time, and the SoC level objectives of EVs when they depart. The fleet operator has full control of the EV charging between the notified arrival and departure time. The charging priority of the EVs is determined by the fleet operator [28]. The EV charging management with direct control was performed to minimize the deviation of the net electricity exchange with the microgrid in the case study for comparison.

Fig. 12 shows the deviation of the net electricity exchange with direct EV charging control. The surplus of the BEMS with the proposed approach (PA) and direct control (DC) is list in Table III. With full control of the EV charging, the case with direct control is able to minimize the deviation of the net electricity exchange to the microgrid. In general, the deviation is even less than the case with the proposed transactive control based approach, although the deviation with the proposed approach is already small. As a result, the penalty from the MGO with direct control is very limited and less than the case with the proposed approach. However, because the management with direct control does not consider the cost of scheduling the EV charging, the reimbursement to the EVs is high in this case. As a result, the total surplus of the BEMS or fleet operator is lower than the case with the proposed approach. It should be noted that the reimbursement to the EVs are estimated according to the response rates of the EVs in the case study. However, due to the fact that the EV owners need to offer complete information and full control permission of the charging in the direct control scheme, they will tend to ask for more reimbursements. In this case, the reimbursements to the EV owners will be even higher with the direct control scheme. On the other hand, the proposed transactive control based approach considers the reimbursements to the EV owners and obtains agreements with the EV owners on the charging dynamically. Thus, although the BEMS is not able to freely manipulate the EV charging demand, it is able to reach an overall optimum with the proposed transactive control based approach.

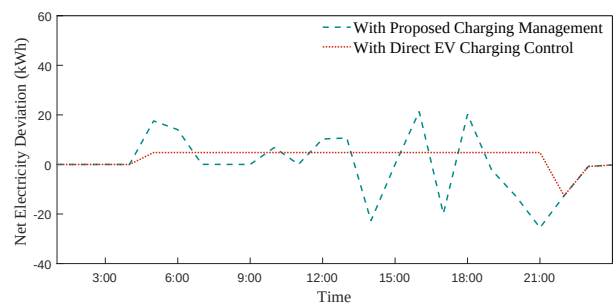


Fig. 12. Net Electricity Exchange Deviation with Direct EV Charging Control.

TABLE III
BALANCE OF BEMS IN REAL TIME OPERATION

Unit: DKK	**PA**	**DC**
Payment for importing electricity	-3250.4	-3273.3
Revenue for exporting electricity	0	0
Charging fee from EVs	5132.5	5183.5
Reimbursement for response to EVs	-33.6	-257.8
Penalty by MGO	-59.4	-28.6
Total	1789.2	1623.8

D. EV Response Analysis

In order to illustrate the response and incentive mechanism of the proposed EV charging framework, the cases of three EVs with different response setting were simulated in the case study. The three EVs are assumed to arrive and start charging at 8 am and plan to leave at 5 pm, and all the SoC levels are assumed to be 50% at the arrival. In the simulation, EV 1 is not willing to respond, its response rate is set zero for all the time. On the other hand, EV 2 is flexible with the charging plan

and its response rate is set to be 800 (kW/DKK). Meanwhile, EV 3 is less responsive and its response rate is set to be 400 (kW/DKK). Nevertheless, EV 3 has a sudden trip plan in real time and sets the response rate to be zero from 11 am in the real-time operation.

The EV charging demand in the simulations is shown in Fig. 13. It is shown that EV 1 are charged as soon as possible from the arrival. It is fully charged at around 10 am. The charging demand of EV 2 are delayed and shifted to the 12th and 14th hour by the BEMS because of its flexibility in the charging. The charging demand of EV 3 is also reduced but to a lower extent in the beginning due to the response setting. However, the charging demand is not reduced from 11 am when EV 3 sets the response rate to zero and requires to be fully charged as soon as possible. Thus, the demand is not reduced anymore in this case.

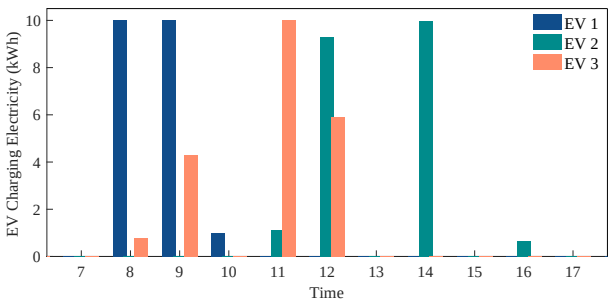


Fig. 13. EV Charging Demand in Real Time.

The SoC levels of the EVs in the simulations are shown in Fig. 14. EV 1 is charged as soon as possible in the simulation. Therefore, its SoC level reaches the maximum level at the earliest time around 10 am. The SoC level of EV 3 increases rapidly after 10 am due to the change of the response setting, and reaches the peak at around 12 am. In contrast, EV 2 are almost fully charged until 2 pm and finally reaches its peak SoC level at around 4 pm. Although the total charging demand of all the three EVs are the same in the simulations, the actual payment of the EVs for the charging are different due to their response provided to the BEMS. The actual charging cost of the EV 1, 2 and 3 in the simulations are 16.8, 15.4 and 15.8 DKK, respectively. EV 1 provides no response to the BEMS and has the highest charging cost. EV 2 is the most responsive in the simulations, and therefore it has the least charging cost. Thus, the proposed framework encourages the EVs to provide as much charging flexibility as possible. Meanwhile, it is able to react to the EV response setting in real time and meet the EV charging requirements in the operation.

E. PV Uncertainty Analysis

In order to illustrate the performance of the proposed framework under different cases of uncertainty, simulations of the proposed framework with 10 different real-time PV output scenarios were conducted. The real-time output of the PV panels in the scenarios is shown in Fig. 15. The root mean squared error (RMSE) of the expectation to the actual real-time output of the PV panels in the scenarios is listed in Table IV.

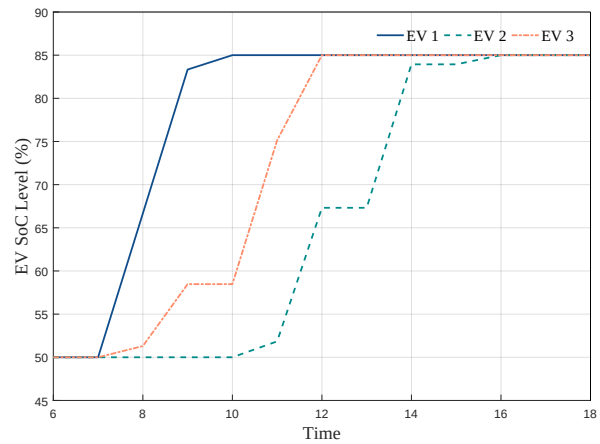


Fig. 14. EV SoC Level in Real Time.

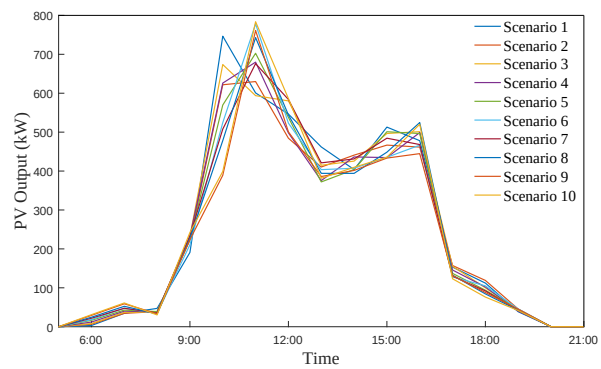


Fig. 15. Output of PV Panels in Scenarios.

TABLE IV
RMSE OF PV OUTPUT IN SCENARIOS

Scenario	RMSE	Scenario	RMSE	Scenario	RMSE
1	19.2kW	5	57.3kW	9	103.6kW
2	34.6kW	6	77.4kW	10	106.3kW
3	23.8kW	7	65.8kW		
4	45.2kW	8	82.5kW		

The surplus of the BEMS in the simulations of the scenarios are shown in Fig. 16. Despite different levels of RMSE of the PV output in the scenarios, the performance of the proposed energy management framework of the BEMS is stable. The solutions with the proposed framework in all the scenarios are very close to the optimal solutions with perfect information. The ratios of the BEMS's surplus with the proposed framework to the optimal solutions in the scenarios are listed in Table V. All the percentages are over 98.5%.

TABLE V
PERCENTAGES OF BEMS'S SURPLUS TO OPTIMAL SOLUTION

Scenario	Ratio	Scenario	Ratio	Scenario	Ratio
1	99.87%	5	98.98%	9	98.55%
2	99.40%	6	99.56%	10	99.30%
3	99.95%	7	99.36%		
4	99.09%	8	98.57%		

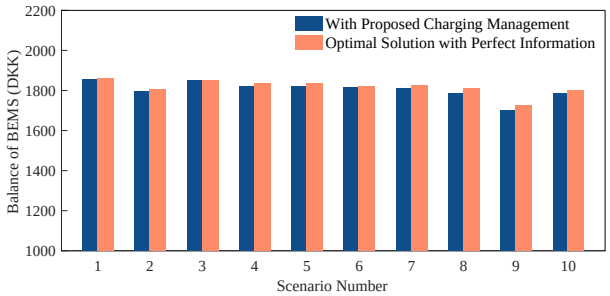


Fig. 16. Balance of BEMS in Scenarios.

V. Conclusions

In this paper, a transactive real-time EV charging management framework is proposed for the BEMS of commercial buildings with on-site PV generation and EV charging services. In the proposed framework, the BEMS employs the EV charging demand to cope with the uncertainties of the PV generation and EV parking activities in the real-time operation. The results of the case studies show that the proposed method is able to provide the charging decisions which are close enough to the optimal solution with perfect forecasts. The proposed elitist GA based algorithm for the transactive control framework is able to perform reliably under uncertainty. The deviation of the BEMS's net electricity exchange with the microgrid from the pre-scheduled plan can be effectively alleviated. The surplus of the BEMS is maximized by the proposed method under the uncertainties of the PV and EVs. The real-time charging requirements, preference setting of the response curves and the required reimbursements for the response of the EV owners are respected by the EV charging decisions while the detailed parking/driving plans of the EV owners are not needed in the proposed transactive charging management framework. Further, the EV owners get reimbursed by the BEMS for their response according to their contributions to the demand management. Meanwhile, the EV owners can adjust their charging requirements and response preferences according to their own needs in the real-time operation so that their willingness to offer the charging management permission to the BEMS of the commercial building is preserved.

References

[1] DNV GL Energy, "A Review of Distributed Energy Resources," New York Independent System Operator, Arlington, VA, Tech. Rep., 2014.

[2] P. Cazzola and M. Gorner, "Global EV Outlook 2016," International Eenergy Agency, Paris, France, Tech. Rep., 2016.

[3] S. M. Frank and P. K. Sen, "Estimation of electricity consumption in commercial buildings," in *Proc. 2011 North American Power Symposium*, Aug 2011, pp. 1–7.

[4] Q. Huang, Q. S. Jia, Z. Qiu, X. Guan, and G. Deconinck, "Matching EV charging load with uncertain wind: A simulation-based policy improvement approach," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1425–1433, May 2015.

[5] H. Yang, H. Pan, F. Luo, J. Qiu, Y. Deng, M. Lai, and Z. Y. Dong, "Operational planning of electric vehicles for balancing wind power and load fluctuations in a microgrid," *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 592–604, April 2017.

[6] G. Li, D. Wu, J. Hu, Y. Li, M. S. Hossain, and A. Ghoneim, "Helos: Heterogeneous load scheduling for electric vehicle-integrated microgrids," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 5785–5796, July 2017.

[7] V. Mohan, J. G. Singh, and W. Ongsakul, "Sortino ratio based portfolio optimization considering EVs and renewable energy in microgrid power market," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 219–229, Jan 2017.

[8] Z. Li, Q. Guo, H. Sun, Y. Wang, and S. Xin, "Emission-concerned wind-EV coordination on the transmission grid side with network constraints: Concept and case study," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1692–1704, Sept 2013.

[9] R. Wang, P. Wang, and G. Xiao, "Two-stage mechanism for massive electric vehicle charging involving renewable energy," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4159–4171, 2016.

[10] Y. Guo, J. Xiong, S. Xu, and W. Su, "Two-stage economic operation of microgrid-like electric vehicle parking deck," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1703–1712, 2016.

[11] W. Wei, F. Liu, and S. Mei, "Charging strategies of EV aggregator under renewable generation and congestion: A normalized nash equilibrium approach," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1630–1641, 2016.

[12] D. Wu, H. Zeng, C. Lu, and B. Boulet, "Two-stage energy management for office buildings with workplace EV charging and renewable energy," *IEEE Trans. Transport. Electrific.*, vol. 3, no. 1, pp. 225–237, March 2017.

[13] N. Liu, Q. Chen, J. Liu, X. Lu, P. Li, J. Lei, and J. Zhang, "A heuristic operation strategy for commercial building microgrids containing EVs and PV system," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2560–2570, April 2015.

[14] J. Tan and L. Wang, "Integration of plug-in hybrid electric vehicles into residential distribution grid based on two-layer intelligent optimization," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1774–1784, July 2014.

[15] H. Liu, Z. Hu, Y. Song, J. Wang, and X. Xie, "Vehicle-to-Grid control for supplementary frequency regulation considering charging demands," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3110 – 3119, 2014.

[16] Z. Li, Q. Guo, H. Sun, S. Xin, and J. Wang, "A new real-time smart-charging method considering expected electric vehicle fleet connections," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 3114–3115, Nov 2014.

[17] W. Qi, Z. Xu, Z. J. M. Shen, Z. Hu, and Y. Song, "Hierarchical coordinated control of plug-in electric vehicles charging in multifamily dwellings," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1465–1474, May 2014.

[18] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, "An optimized EV charging model considering TOU price and SOC curve," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 388–393, March 2012.

[19] J. Tan and L. Wang, "Enabling reliability-differentiated service in residential distribution networks with PHEVs: A hierarchical game approach," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 684–694, March 2016.

[20] Z. Liu, Q. Wu, S. Huang, and H. Zhao, "Transactive energy: A review of state of the art and implementation," in *Proc. 12th IEEE PowerTech Manchester*, Manchester, UK, 2017, pp. 1–6.

[21] N. Liu, X. Yu, C. Wang, and J. Wang, "Energy sharing management for microgrids with PV prosumers: A stackelberg game approach," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1088–1098, June 2017.

[22] B. Kouvaritakis and M. Cannon, *Model Predictive Control, Classical, Robust and Stochastic*. Springer, 2016.

[23] A. J. Umbarkar and M. S. Joshi, "Review of Parallel Genetic Algorithm Based on Computing Paradigm and Diversity in Search Space," *ICTACT Journal on Soft Computing*, vol. 03, no. 04, pp. 615–622, 2013.

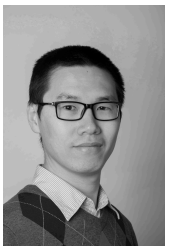
[24] S. Cavuoti, M. Garofalo, M. Brescia, A. Pescape, G. Longo, and G. Ventre, "Genetic Algorithm Modeling with GPU Parallel Computing Technology," *Smart Innovation, Systems and Technologies*, vol. 19, pp. 29–39, 2013.

[25] P. Pospichal, J. Jaros, and J. Schwarz, "Parallel Genetic Algorithm on the CUDA Architecture," in *Proc. European Conference on the Applications of Evolutionary Computation*, Istanbul, Turkey, April 2010, pp. 442–451.

[26] Q. Wu, A. H. Nielsen, J. Ostergaard, S. T. Cha, F. Marra, Y. Chen, and C. Traeholt, "Driving Pattern Analysis for Electric Vehicle (EV) Grid Integration Study," in *Proc. 2010 IEEE PES Innovative Smart Grid Technologies Conf. Europe (ISGT Europe)*, Oct 2010, pp. 1–6.

[27] S. I. Vagropoulos, D. K. Kyriazidis, and A. G. Bakirtzis, "Real-Time Charging Management Framework for Electric Vehicle Aggregators in a Market Environment," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 948–957, 2016.

[28] Y. Zheng and L. Jian, "Smart charging algorithm of electric vehicles considering dynamic charging priority," in *Proc. 2016 IEEE International Conference on Information and Automation*. Ningbo, China: IEEE, 2016, pp. 555–560.



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