Transactive Charging Management of Electric Vehicles in Office Buildings: A Distributionally Robust Chance-Constrained Approach

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Transactive charging management of electric vehicles in office buildings: a distributionally robust chance-constrained approach

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Abstract

In this paper, a new energy management model is proposed to determine the optimal scheduling of an office building which includes electric vehicle (EV) charging piles, batteries, and rooftop photovoltaic systems. To optimally manage the electricity procurement of the building and mitigate the rate of transformer aging, the building energy management system (BEMS) employs the flexibility of batteries and EV charging. In the proposed model, to incentivize EV owners to offer their flexibility, the BEMS organizes a transactive market among plugged-in EVs. To this end, EV owners submit their response curves and the target state-of-charge to the BEMS. Then, the transactive market is cleared to determine the market-clearing price for each EV, the optimal EV charging decisions, and accordingly, the scheduling of office building. Also, to model the correlated uncertainties of solar power generation and demand, the distributionally robust chance-constrained method is employed. Moreover, the "Big-M" technique and the piecewise linear approximation method are utilized to linearize the optimization problem. Finally, the case of a building with 100 charging piles is studied. The numerical results illustrate a decrease in the total operating cost of BEMS and the rate of transformer aging compared to uncontrolled charging and direct control approaches.

Keywords: Transactive market, building energy management, electric vehicle, transformer aging, distributionally robust chance-constrained

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Nomenclature

A. Sets and indices

V	Set of EVs, indexed by v
T	Set of time intervals, indexed by t

B. Parameters and constants

$\mathcal{T}$	Transactive market time interval
$P_v^{r,EV}$	Rated charging power of EV battery v
$P^{r,BB}$	Rated power of building battery
γ	Base rate for EV charging
λ_v^{max}	Required reimbursement for response $\Delta P = P_v^r$
LMP_t/FIT_t	Price for buying/selling electricity from/to the main grid at time t
PD_t	Non-responsive demand at time t
PV_t	solar power generation at time t
E_v^{EV}	Energy capacity of EV battery v
E^{BB}	Energy capacity of building battery
$\overline{P}_{up}$	Limitation of energy exchange with the main grid
η_v^{EV}	Charging efficiency of EV battery v
$\eta^{ch/dis,BB}$	Charging/Discharging efficiency of battery
$SOC^{min/max}$	Minimum/Maximum level of SOC
$SOC^{ini/tar}$	Initial/Target level of SOC

$s_{v,t}$	EV parking status at time t
C_{BAC}	Degradation cost coefficient of battery
t_a, t_d	Arrival time and departure time
θ_t^A	Ambient temperature at time t
$\Delta\theta^{TR/TH}$	Rated top-oil temperature rise over ambient temperature/Rated conductor temperature rise over top-oil temperature
R	Ratio of load losses at rated load to no-load
NIL	Normal insulation life
LOL^{max}	Allowable transformer's loss of life factor

C. Variables

$SOC_{v,t}^{EV}$	SOC of EV battery v at time t
SOC_t^{BB}	SOC of building battery at time t
$\Delta P_{v,t}^{max}$	Maximum offered flexibility of EV battery v at time t
$\Delta P_{v,t}^{cl}$	Reduced charging power of EV battery v at time t
$P_{v,t}^{ch,EV}$	Charging power of EV battery v at time t
$P_t^{ch/dis,BB}$	Charging/Discharging power of building battery at time t
$P_t^{buy/sell}$	Buying/Selling energy from/to the main grid at time t
Γ_t	Binary variable represents the direction of exchanged power with the main grid at time t
Λ_t	Binary variable represents the charge/discharge state of battery at time t
DC_t^{BB}	Degradation cost of battery at time t

$\lambda^{cl}_{v,t}$	Clearing price of EV battery v at time t
F^{AA}_t	Aging acceleration factor at time t
θ^H_t	Hottest spot temperature at time t
$\Delta\theta^{TO}_t$	Top-oil temperature rise over ambient temperature at time t
LOL	Transformer's loss of life factor

1. Introduction

Widespread deployment of small-scale distributed energy resources (DERs), particularly electric vehicles (EVs), at the demand side of power systems has changed the operation and characteristics of distribution systems [1]. Although EVs have vast benefits such as reducing air pollution and society's reliance on fossil fuels, the uncontrolled charging of a large population of EVs will potentially create significant negative impacts on the operation of distribution systems [2, 3]. A review of [4] and [5] indicates that uncontrolled charging of EVs will impose new peak loads on distribution systems. Once these new peak loads coincide with the maximum demand of other electrical loads, it can provoke several problems such as distribution transformer overloading as a primary concern [6]. Since the capacity of distribution transformers is commonly chosen according to peak loads of the connected homes, overloading caused by uncontrolled charging of EVs leads to an acceleration of transformers aging and eventual early failure [7].

In the literature, several methods and approaches have been proposed to control EV charging loads. These approaches are categorized into four classes [8]: incentive-based demand response (DR) [9], price-based DR [10], centralized optimization [11], and transactive energy (TE). Authors in [9] proposed an incentive-based DR operation method for EV charging to manage the distribution system stability and renewable energy curtailment. In [10], a price-based method for the coordination of EV charging has been proposed to mitigate peak load and prevent transformer overloading. A multi-objective control and regulation algorithm was proposed in [11] to balance generation and demand through the bidirectional control of energy flows. Among the above-mentioned energy management approaches, the TE that fully utilizes the response potential of flexible DERs using market-based mechanisms is the most efficient method that yields distinct benefits [12]. The TE provides a new jointly economic and control platform that enables independent agents to trade energy within distribution systems. Thus, using the TE method, EVs can directly participate in the local electricity markets to achieve optimal real-time charge/discharge decisions through an exchange of value-based information [13, 14].

Over the past years, several works have proposed various TE frameworks to optimally control EV charging. The work in [15] presented a TE concept-based EV charging management scheme for commercial parking lots equipped with photovoltaic on-site generation. In [16], a linear programming (LP)-based TE model was proposed to enable the EV aggregators' participation in the local energy market considering the distribution network topology. A bi-level TE market framework was proposed in [17] to optimize the energy trading between EV charging stations equipped with rooftop solar units. The work in [18] proposed a day-ahead market platform for EV aggregators to alleviate congested feeders in smart distribution networks. Although these reviewed works achieve benefits for aggregators and system operators, the active participation of EVs in the local energy market has not been considered.

In addition, the authors in [19] proposed a real-time transactive EV charging management framework that enables the active participation of EV owners in the local electricity market. In [20], a TE-based charging control scheme was developed to determine the optimal charge/discharge decisions of EVs with a voltage control system. An iterative algorithm for transactive charging management of EVs with mitigating the voltage unbalance was proposed in [21]. In the above-reviewed TE models [19–21], the retail market operator clears the real-time market after estimating the EV owners' bids and offers price-quantity. Authors in [22] developed a market platform that enables EVs to offer their flexibility at the distribution grid level to avoid grid reinforcement necessity. Although these studies have properly taken into account the active participation of individual EV owners in the TE market, the impact of uncertainties associated with solar power generation, demand, and EV owners' activities on the market operation has not been considered.

To model the uncertainties in the operation of power systems, several methods have been developed such as stochastic programming (SP) and robust optimization (RO) [23]. Authors in

[24–26] utilized the SP approach to model the prevailing uncertainties in the energy management problem. The work in [24] developed a stochastic scenario-based model to manage the uncertainties of solar power generation using the flexibility of EV batteries. Authors in [25] presented a stochastic two-stage optimization problem to achieve the optimal charge/discharge decisions of EVs in the residential building. In [26], a stochastic mixed-integer linear programming (MILP) model was developed to manage flexible demand, storage devices, and EVs in cooperative energy communities. The major drawback of the SP approach is its running time and computational complexity which addresses by employing the scenario reduction method. Thus, SP approaches give less realistic solutions due to eliminating lots of scenarios during the scenario reduction procedure and ignoring the occurrence of some states for the uncertainty in solving the optimization problem.

Moreover, authors in [27] presented an RO-based charging control model for EVs in low voltage distribution systems considering the uncertainties associated with the mobility behavior of EV drivers. A multi-objective RO-based approach was proposed in [28] to manage smart buildings under uncertainties of renewable energy sources (RESs) and electricity demand. RO approaches can not model the stochastic nature of the uncertainties that are subject to the high fluctuation during a day such as solar power generation and demand. To address this challenge, some studies in the literature have utilized the distributionally robust chance-constrained (DRCC) method [29–31]. Compared to the RO, the DRCC approach considers the worst probability distribution function rather than the worst-case situation. This consideration provides more realistic solutions compared to SP and RO approaches due to considering the benefits of both approaches.

In [29], the DRCC method was employed to model the uncertainty of solar power generation in the operation of building energy management systems. In that study, the DR program has been applied to the building appliances through load shifting and curtailment. Authors in [30] proposed a DRCC model based on the TE approach to optimally schedule a multi-carrier energy microgrid under uncertainties of RESs as well as natural gas and electricity market prices. A DRCC-based energy management model to maximize the profit of retailers considering uncertainties of renewable generation and electricity demand was proposed in [31]. These reviewed

Table 1: Taxonomy of research works in the realm of TE management frameworks.

Ref.	Participation of EV owners	Transformer aging	Uncertainty modeling	Correlated Uncertainty	Optimization problem
[15]	-	-	SP	-	MILP
[16]	-	-	-	-	LP
[17]	-	-	-	-	heuristic iterative
[18]	-	-	-	-	NLP
[19]	✓	-	-	-	MILP
[20]	✓	-	-	-	MILP
[21]	✓	-	-	-	heuristic iterative
[24]	✓	-	SP	-	MINLP
[25]	✓	-	SP	-	MILP
[26]	-	-	SP	-	MILP
[27]	-	-	RO	-	LP
[28]	-	-	RO	-	MILP
[29]	-	-	DRCC	-	MILP
[30]	-	-	DRCC	-	MINLP
[31]	-	-	DRCC	-	MILP
This work	✓	✓	DRCC	✓	MILP

studies have proved the high efficiency of using the DRCC approach by providing numerical analyses and illustrating the capability of this approach in uncertainty modeling to achieve the research objectives.

In summary, table 1 compares the related works reviewed above in terms of enabling active participation of EV owners, considering the transformer aging, uncertainty modeling, considering the correlation between uncertain parameters, and mathematical formulation of the optimization problem. As observed from this table, none of the above-reviewed studies have considered transformer aging and correlated uncertainties in the TE-based charging management of EVs. Moreover, a few works have considered the active participation of EV owners in the energy management problem in which the prevailing uncertainties were not modeled or simply modeled by defining a set of scenarios. To this end, this paper proposes a DRCC-based energy management model for office buildings that allows EV owners to actively participate in the transactive market. The proposed model employs the flexibility of EV charging and building batteries to minimize the total operating cost of BEMS considering the constraint of the transformer's loss of life. It is to be noted that the BEMS acts as the owner of building batteries and has full control permission on the scheduling of these resources. However, similar control permission on the EV batteries is not available to the BEMS. Thus, the EV owners must be encouraged with incentives to change their charging patterns (delaying the charging). Further, each EV owner requires different reimbursement for its response that is presented by means of the response curve. To this end, the EV owners individually determine their response curves, i.e., the required reimbursement for the response to the price signal, and the target level of state-of-charge (SOC) at departure, and submit this information to the BEMS. Then, the BEMS solves an optimization problem to determine the transactive market clearing prices, EV charging decisions, scheduling of building batteries, and accordingly, the scheduling of office building. Due to the non-linearities associated with the proposed EV owner's response curve and the transformer's loss of life, the original optimization model is formulated as a mixed-integer non-linear programming (MINLP) problem. To mitigate the computational burden, this model is recast into MILP one using appropriate linearization methods. Also, to model the uncertainties of solar power generation and demand as well as their mutual correlation in the scheduling problem, the DRCC method is employed. The utilized uncertainty modeling approach not only considers the stochastic nature of uncertainties but also guarantees a specific amount of economic benefit for the BEMS of an office building with a certain probability. The main contributions of this paper are outlined as follows.

- This study proposes a transactive charging management framework to enable the active participation of EV owners in the local energy market. In this paper, unlike [24], in which a complicated response curve has been proposed, a new response curve model is developed that can be easily submitted to the BEMS by adjusting the required price of the EV owner for the maximum response.

- Unlike most reviewed studies in which the impact of uncertainties on the transactive market operation has not been taken into account, we employ the DRCC method to model the uncertainties associated with solar power generation and demand and their mutual correlation.

- The aging of distribution transformer due to overloading is properly considered in the proposed energy management model. Incorporating this term is inevitable in practice with the increasing penetration of EVs in distribution systems.

- To mitigate the computational burden and improve the accuracy of the solution, the original MINLP model is recast into the MILP problem by linearizing the non-linear terms associated with the proposed response curve and transformer's loss of life using the "Big-M" and piecewise linear approximation techniques.

The rest of this paper is organized as follows. Section 2 provides the general structure of the proposed TE market and EV owners' response curves. The optimization framework and linearization procedure to determine the scheduling of BEMS are expressed in Section 3. Section 4 represents the simulation assumptions, numerical results, and discussions. Finally, the conclusion is drawn in Section 5.

2. TE Market Framework

Figure 1 depicts the conceptual framework of the proposed energy management model. In the presented framework, the distribution system operator (DSO) acts as the leader of the system operation and sends the day-ahead price signals to the BEMSs of office buildings. Then, each BEMS, which is the follower in the proposed system operation, reacts to the received price signal and determines its scheduling under the uncertainties of solar power generation and demand. In this study, we have focused on an individual BEMS of the office building which tries to minimize its total operating cost considering the constraint of the distribution transformer's loss of life by employing the flexibility of building batteries and EV charging. As shown in this figure, to employ the flexibility of EV charging, the BEMS organizes a transactive market among plugged-in EVs. The proposed transactive market allows EV owners to offer their charging flexibility and get reimbursed accordingly. For this purpose, EV owners submit their response curves and target levels of SOC at departure to the BEMS. The response curve of the EV owner that represents the required reimbursement for different values of response is shown in Figure 2. As seen in this figure, each EV owner individually can determine its response curve by setting the parameters

λ_v^{max} (required reimbursement for the maximum response) and P_v^r (rated charging power of EV). The value of P_v^r is constant, and therefore, each EV owner can submit its preferred response curve to the BEMS in a user-friendly manner by setting the parameter λ_v^{max}.

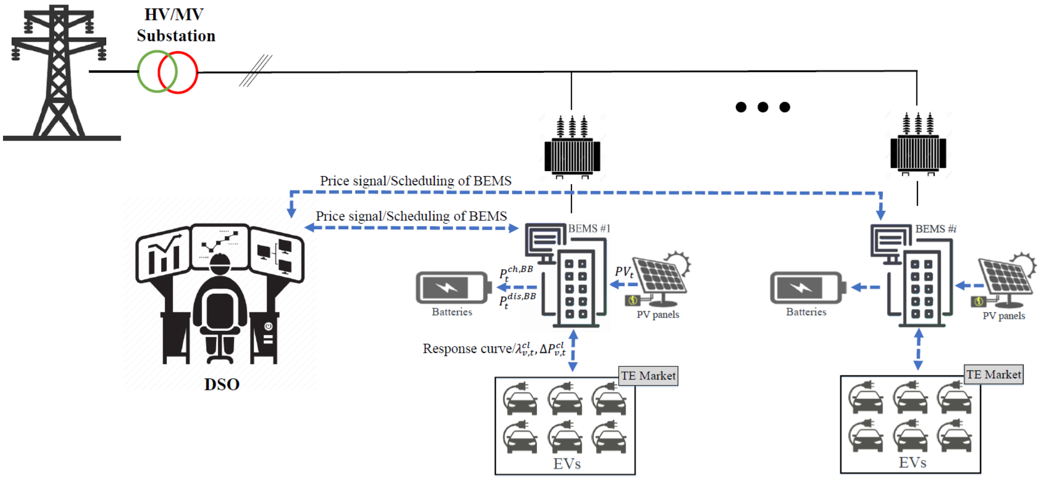

Figure 1: The conceptual structure of the proposed control model

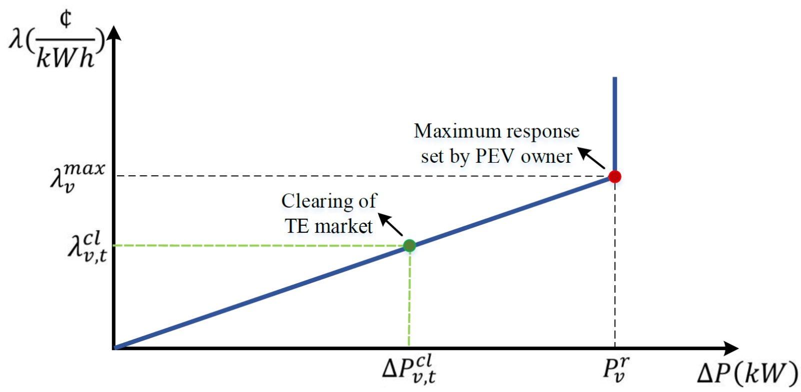

Figure 2: Response curve of the EV owner

Without any smart charging algorithms, the EV battery is charged as soon as possible with the base charging price till achieving the target SOC level. On the other hand, with the proposed transactive charging management model, the EV owners allow the BEMS to decrease the charging power of EV batteries based on their submitted response curves for reimbursement. Hence, the charging power of EV battery is calculated as follows.

$$P_{v,t}^{ch,EV} = \Delta P_{v,t}^{max} - \Delta P_{v,t}^{cl} \tag{1}$$

$$\Delta P_{v,t}^{max} = \lfloor P_v^{r,EV}, \frac{(SOC_v^{tar} - SOC_{v,t}^{EV})E_v^{EV}}{\eta^{EV}\mathcal{T}} \rfloor \tag{2}$$

where $\lfloor . \rfloor$ represents the min function and $\Delta P_{v,t}^{max}$ is the allowable charging power of EV battery v at time t that is the minimum value between rated charging power of EV and the possible charging power based on the residual capacity of EV battery.

After submitting the response curves, the BEMS solves its optimization problem to clear the transactive market and determine the market clearing price. According to the clearing price and using the response curve, the decreased charging power of EVs is determined. It is to be noted that, the maximum offered flexibility of EV battery v at corresponding time t is equal to $\Delta P_{v,t}^{max}$. For example, once the EV battery achieves the target level of SOC ($SOC_{v,t} = SOC_v^{tar}$), the maximum flexibility that the corresponding EV can offer will be equal to zero. Thus, the response curve of EV battery is formulated as (3).

$$\Delta P_{v,t}^{cl} = \begin{cases} k_v \lambda_{v,t}^{cl} & \lambda_{v,t}^{cl} < \frac{1}{k_v}\Delta P_{v,t}^{max} \\ \Delta P_{v,t}^{max} & \lambda_{v,t}^{cl} \geq \frac{1}{k_v}\Delta P_{v,t}^{max} \end{cases} \tag{3}$$

In above k_v is the inverse of the response curve's slope that is computed as $k_v = P_v^r/\lambda_v^{max}$. When the optimization problem is solved and accordingly the transactive market clearing price and the decreased EV batteries' charging power are obtained, the actual payment for charging of EV battery v at time t ($Pay_{v,t}$) can be computed by subtracting the reimbursement to the EV owner ($Reimb_{v,t}$) from the charged energy cost ($CC_{v,t}$) as (4).

$$Pay_{v,t} = CC_{v,t} - Reimb_{v,t} \tag{4}$$

where the reimbursement to the EV owner for the flexibility and the charged energy cost are calculated as (5).

$$
\begin{aligned}
Reimb_{v,t} &= \lambda^{cl}_{v,t} \Delta P^{cl}_{v,t} \mathcal{T} \\
CC_{v,t} &= \gamma P^{ch,EV}_{v,t} \mathcal{T}
\end{aligned}
\tag{5}
$$

3. Building Energy Management Model

In this Section, the mathematical formulation of the proposed TE management model is presented. For a better understanding, first, the optimization problem of the proposed model without considering the prevailing uncertainties is presented. After that, the uncertainties of solar power generation and demand are modeled in the presented problem using the DRCC method.

3.1. Deterministic Model

The deterministic optimization problem of the proposed transactive charging management model is formulated as follows.

$$
\begin{aligned}
min \quad & \sum_{t \in T} \Big[(LMP_t P^{buy}_t \mathcal{T} - FIT_t P^{sell}_t \mathcal{T}) - \\
& \sum_{v \in V} (\gamma P^{ch,EV}_{v,t} \mathcal{T} - Reimb_{v,t} \mathcal{T}) + DC^{BB}_t \mathcal{T} \Big]
\end{aligned}
\tag{6}
$$

Subject to:

$$
Reimb_{v,t} = \lambda^{cl}_{v,t} \Delta P^{cl}_{v,t} \tag{7}
$$

$$
DC^{BB}_t = C_{BAC} (P^{ch,BB}_t \eta^{ch,BB} + P^{dis,BB}_t / \eta^{dis,BB}) \tag{8}
$$

$$
P^{buy}_t - P^{sell}_t = \sum_{v \in V} P^{ch,EV}_{v,t} + PD_t - PV_t + P^{ch,BB}_t - P^{dis,BB}_t \tag{9}
$$

$$
0 \leq P^{buy}_t \leq \overline{P}_{up} \Gamma_t \tag{10}
$$

$$0 \leq P_t^{sell} \leq \overline{P}_{up}(1 - \Gamma_t) \tag{11}$$

$$P_{v,t}^{ch,EV} = (\Delta P_{v,t}^{max} - \Delta P_{v,t}^{cl}) s_{v,t} \tag{12}$$

$$\Delta P_{v,t}^{cl} = \begin{cases} k_v \lambda_{v,t}^{cl} & \lambda_{v,t}^{cl} < \frac{1}{k_v} \Delta P_{v,t}^{max} \\ \Delta P_{v,t}^{max} & \lambda_{v,t}^{cl} \geq \frac{1}{k_v} \Delta P_{v,t}^{max} \end{cases} \tag{13}$$

$$\Delta P_{v,t}^{max} = \min\{P_v^{r,EV}, \frac{\left(SOC_v^{tar} - SOC_{v,t}^{EV}\right) E_v^{EV}}{\eta^{EV} \mathcal{T}}\} \tag{14}$$

$$SOC_{v,t}^{EV} = SOC_{v,t-1}^{EV} + \frac{P_{v,t}^{ch,EV} \eta^{EV} \mathcal{T}}{E_v^{EV}} \tag{15}$$

$$SOC_v^{min,EV} \leq SOC_{v,t}^{EV} \leq SOC_v^{max,EV} \tag{16}$$

$$SOC_{v,t_a}^{EV} = SOC_v^{ini,EV} \tag{17}$$

$$SOC_{v,t_d}^{EV} = SOC_v^{tar} \tag{18}$$

$$0 \leq P_t^{ch,BB} \leq P^{r,BB} \Lambda_t \tag{19}$$

$$0 \leq P_t^{dis,BB} \leq P^{r,BB}(1 - \Lambda_t) \tag{20}$$

$$SOC_t^{BB} = SOC_{t-1}^{BB} + \frac{(P_t^{ch,BB} \eta^{ch,BB} - P_t^{dis,BB} / \eta^{dis,BB}) \mathcal{T}}{E^{BB}} \tag{21}$$

$$SOC^{min,BB} \leq SOC_t^{BB} \leq SOC^{max,BB} \tag{22}$$

$$SOC_1^{BB} = SOC^{ini,BB} \tag{23}$$

$$LOL \leq LOL^{max} \tag{24}$$

$$LOL = \frac{\sum_{t \in T} F_t^{AA} \mathcal{T}}{NIL} \tag{25}$$

$$F_t^{AA} = exp(\frac{15000}{110 + 273} - \frac{15000}{\theta_t^H + 273}) \tag{26}$$

$$\theta_t^H = \theta_t^A + \Delta\theta_t^{TO} + \Delta\theta_t^H \tag{27}$$

$$\Delta\theta_t^{TO} = \Delta\theta^{TR}(\frac{K_t^2 R + 1}{R + 1})^n \tag{28}$$

$$\Delta\theta_t^H = \Delta\theta^{TH}(K_t^2)^m \tag{29}$$

The objective of BEMS's scheduling (6) is to minimize its cost including four terms. The first and the second terms are respectively the cost and revenue of exchanged electricity with the main grid. The third term is the payment of EVs to the BEMS that its value is the charged energy cost minus the reimbursement to the EVs in the TE market (7). The fourth term is the degradation cost of building batteries that is calculated as (8). It is worth mentioning that the battery will degrade with the charging and discharging process. Thus, the degradation cost of batteries must be taken into consideration in the energy management problem. In this paper, we select a linear model to compute the battery degradation cost [32].

The equality constraint (9) provides the power balance between generation and demand of the building. Equations (10) and (11) are presented to prevent the simultaneous import/export power from/to the main grid. Further, equations (12)-(18) provide the constraints associated with EVs. The charging power of the EV batteries is determined by (12) as well as the response curve of EVs is expressed as (13). Equation (14) calculates the maximum offered flexibility of the EV battery at each time interval, and (15) represents the hourly energy balance in the EV batteries. The allowable range of SOC for EV batteries is shown as (16), and the initial and target levels of SOC respectively at arrival and departure times are expressed as (17) and (18), respectively. It is worth mentioning that since the arrival and departure times of employees (EV owners) can be forecasted with high accuracy, the uncertainties associated with EV owners' arrival and departure times are neglected. Also, it is assumed that each EV owner upon departure submits the target SOC for the next day.

Moreover, equations (19)-(23) represent the constraints of building batteries. Constraints (19) and (20) limit the charging and discharging power of EV batteries, respectively. The hourly energy balance and the allowable range of SOC level in EV batteries are represented as (21) and (22), and the initial value of SOC level in building batteries is shown as (23). Moreover, equations (24)-(29) represent the constraints associated with the distribution transformer's loss of life. In this regard, constraint (24) retains the transformer's loss of life factor within the allowable limit set by IEEE standard C 57.91 [33]. Note that the transformer's loss of life factor is calculated as (25)-(29).

In the above formulation, (7), (13), (14), and transformer's loss of life equations are non-linear. To mitigate the computational complexity and find the global solution using available solvers, these non-linear equations are linearized as follows.

3.1.1. Linearization of (7)

For linearizing this equation, first, the continuous variable $\lambda^{cl}_{v,t}$ is approximated to an integer variable using definition of a set of binary variables $\Psi_{i,v,t}$. Thus, (7) is expressed as follows.

$$Reimb_{v,t} = \lambda^{cl}_{v,t}\Delta P^{cl}_{v,t} = \sum_{i\in I} 2^{i-1}\Psi_{i,v,t}\Delta P^{cl}_{v,t} \tag{30}$$

Suppose $\Psi_{i,v,t}\Delta P^{cl}_{v,t} = \Phi_{i,v,t}$, by means of the "Big-M" method, the non-linear equation is linearized as follows.

$$\lambda^{cl}_{v,t} = \sum_{i\in I} 2^{i-1}\Psi_{i,v,t} \tag{31}$$

$$Reimb_{v,t} = \sum_{i\in I} 2^{i-1}\Phi_{i,v,t} \tag{32}$$

$$0 \leq \Phi_{i,v,t} \leq \Psi_{i,v,t}M_1 \tag{33}$$

$$\Delta P^{cl}_{v,t} - (1-\Psi_{i,v,t})M_1 \leq \Phi_{i,v,t} \leq \Delta P^{cl}_{v,t} \tag{34}$$

3.1.2. *Linearization of* (13)

For linearizing this equation, a binary variable $N_{v,t}$ is employed. Hence, this equation can be formulated as follows.

$$\Delta P^{cl}_{v,t} = k_v\lambda^{cl}_{v,t}N_{v,t} + \Delta P^{max}_{v,t}(1-N_{v,t}) \tag{35}$$

$$\lambda^{cl}_{v,t} \geq \frac{1}{k_v}\Delta P^{max}_{v,t}(1-N_{v,t}) - M_2 N_{v,t} \tag{36}$$

$$\lambda^{cl}_{v,t} < \frac{1}{k_v}\Delta P^{max}_{v,t}N_{v,t} + M_2(1-N_{v,t}) \tag{37}$$

In the above equations, the products of binary variable $N_{v,t}$ and continuous variables $\lambda^{cl}_{v,t}$ and $\Delta P^{max}_{v,t}$ creates non-linearity. Using auxiliary continuous variables $\Omega_{v,t} = \lambda^{cl}_{v,t}N_{v,t}$ and $\Upsilon_{v,t} = \Delta P^{max}_{v,t}N_{v,t}$, these equations are replaced as follows.

$$\Delta P^{cl}_{v,t} = k_v \Omega^{cl}_{v,t} + \Delta P^{max}_{v,t} - \Upsilon_{v,t} \tag{38}$$

$$\lambda^{cl}_{v,t} \geq \frac{1}{k_v}(\Delta P^{max}_{v,t} - \Upsilon_{v,t}) - M_2 N_{v,t} \tag{39}$$

$$\lambda^{cl}_{v,t} < \frac{1}{k_v}\Upsilon_{v,t} + M_2(1 - N_{v,t}) \tag{40}$$

$$0 \leq \Omega_{v,t} \leq N_{v,t} M_3 \tag{41}$$

$$\lambda^{cl}_{v,t} - (1 - N_{v,t})M_3 \leq \Omega_{v,t} \leq \lambda^{cl}_{v,t} \tag{42}$$

$$0 \leq \Upsilon_{v,t} \leq N_{v,t} M_4 \tag{43}$$

$$\Delta P^{max}_{v,t} - (1 - N_{v,t})M_4 \leq \Upsilon_{v,t} \leq \Delta P^{max}_{v,t} \tag{44}$$

3.1.3. Linearization of (14)

This constraint can be recast as a two-conditional equation as:

$$\Delta P^{max}_{v,t} = \begin{cases} \frac{(SOC^{tar}_v - SOC^{EV}_{v,t})E^{EV}_v}{\eta^{EV}\mathcal{T}} & \frac{(SOC^{tar}_v - SOC^{EV}_{v,t})E^{EV}_v}{\eta^{EV}\mathcal{T}} < P^{r,EV}_v \\ P^{r,EV}_v & \frac{(SOC^{tar}_v - SOC^{EV}_{v,t})E^{EV}_v}{\eta^{EV}\mathcal{T}} \geq P^{r,EV}_v \end{cases} \tag{45}$$

For linearizing the above equation, the binary variable $Q_{v,t}$ is employed. Thus, constraint (14) is replaced by the following constraints.

$$\Delta P^{max}_{v,t} = (1 - Q_{v,t})P^{r,EV}_v + Q_{v,t}\frac{\left(SOC^{tar}_v - SOC^{EV}_{v,t}\right)E^{EV}_v}{\eta^{EV}\mathcal{T}} \tag{46}$$

$$\frac{\left(SOC_v^{tar} - SOC_{v,t}^{EV}\right) E_v^{EV}}{\eta^{EV} \mathcal{T}} \geq (1 - Q_{v,t}) P_v^{r,EV} - M_5 Q_{v,t} \tag{47}$$

$$\frac{\left(SOC_v^{tar} - SOC_{v,t}^{EV}\right) E_v^{EV}}{\eta^{EV} \mathcal{T}} < Q_{v,t} P_v^{r,EV} + M_5 (1 - Q_{v,t}) \tag{48}$$

The product of binary variable $Q_{v,t}$ to continuous variable $SOC_{v,t}^{EV}$ makes (46) non-linear. Suppose $Q_{v,t} SOC_{v,t}^{EV} = X_{v,t}$, then, (46) can be linearized as follows.

$$\Delta P_{v,t}^{max} = (1 - Q_{v,t}) P_v^{r,EV} + \frac{(Q_{v,t} SOC_v^{tar} - X_{v,t}) E_v^{EV}}{\eta^{EV} \mathcal{T}} \tag{49}$$

$$0 \leq X_{v,t} \leq Q_{v,t} M_6 \tag{50}$$

$$SOC_{v,t}^{EV} - (1 - Q_{v,t}) M_6 \leq X_{v,t} \leq SOC_{v,t}^{EV} \tag{51}$$

3.1.4. Linearization of transformer's loss of life constraints

Non-linear constraints (26)-(29) for calculation of transformer's loss of life represent the aging acceleration factor (F_t^{AA}) as an exponential function of transformer loading (K_t), i.e., $F_t^{AA} = exp(a + b/K_t^c + d)$ where a, b, c, and d are constants. This function can be approximated using the piecewise linear approximation method as shown in Figure 3 as follows [34].

$$\tilde{F}_t^{AA} = \alpha_{k,t} K_t - \beta_{k,t}, K_t^{k-1} \leq K_t \leq K_t^k, k = 1, ..., M \tag{52}$$

where M is the number of segments.

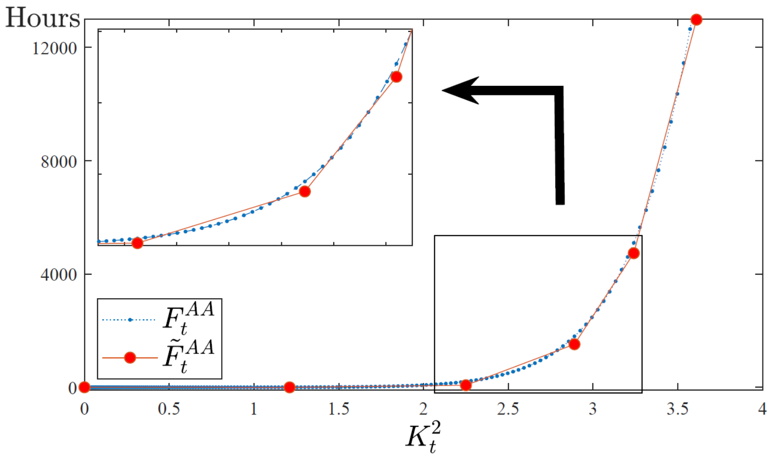

Figure 3: Aging acceleration factor F_t^{AA} and its piecewise approximation $\tilde{F}_t^{AA}$

Finally, using the linearized expressions above, the MILP model is as follows.

$$Eq.\ (6) \tag{53}$$

Subject to:

$$Eqs.\ (8) - (12),\ (15) - (25) \tag{54}$$

$$Eqs.\ (31) - (34),\ (38) - (44),\ (47) - (52) \tag{55}$$

3.2. DRCC-based Model

The proposed deterministic MILP model (53)-(55) should be developed to incorporate the prevailing uncertainties. The main uncertainties in this work are the solar power generation and demand which are highly correlated [35]. Thus, the DRCC method is employed to incorporate the uncertainties such that the constraints subject to uncertainty will be satisfied within a confidence set and would be robust against all probability distribution functions corresponding to random variables [30].

Since the solar power generation and demand (i.e., $\tilde{PD}_t$ and $\tilde{PV}_t$) are uncertain parameters, we formulate the power balance constraint (9) based on DRCC approach $\forall t \in T$ as follows [32, 36].

$$\inf_{\mathbb{P}\in\mathcal{D}} \mathbb{P}\Big(P_t^{buy} - P_t^{sell} - \sum_{v\in V} P_{v,t}^{ch,EV} - P_t^{ch,BB} + P_t^{dis,BB} \geq \tilde{PD}_t - \tilde{PV}_t\Big) \geq 1 - \epsilon \tag{56}$$

where $\mathcal{D}$ is the confidence set that represents the family of all distributions that have the same moment information such as mean, variance, and covariance [30]. The inf operator determines the worst distribution in the confidence set for which the above constraint must be satisfied. The confidence set can be represented as follows.

$$\mathcal{D} = \Big\{\mathbb{P} \in \mathcal{M}_+ : \mathbb{E}_{\mathbb{P}}[\tilde{\zeta}_t] = \tilde{\mu}_t, \mathbb{E}_{\mathbb{P}}[(\tilde{\zeta}_t - \tilde{\mu}_t)(\tilde{\zeta}_t - \tilde{\mu}_t)^T] = \tilde{\Sigma}_t\Big\} \tag{57}$$

In above $\mathcal{M}_+$ denotes the set of all probability distribution functions. Moreover, $\tilde{\zeta}_t = [\tilde{PD}_t, \tilde{PV}_t]$ is the vector of uncertain parameters with the first and second moments of $\tilde{\mu}_t$ and $\tilde{\Sigma}_t$, respectively. Since the uncertainties arising from the demand and solar power generation are primarily driven by forecast errors, in this work, the uncertain parameters $\tilde{\zeta}_t$ are modeled as the sum of the forecasted values $\overline{\zeta}_t$ and the random variable ζ_t as:

$$\tilde{\zeta}_t = \overline{\zeta}_t + \zeta_t;\ \ \forall t \in T \tag{58}$$

where ζ_t follows an unknown probability distribution with zero mean ($\mu_t = 0$) and covariance matrix Σ_t as:

$$\Sigma_t = \begin{bmatrix} \left(\sigma_t^d\right)^2 & \sigma_t^d \sigma_t^{pv} \rho_t \\ \sigma_t^d \sigma_t^{pv} \rho_t & \left(\sigma_t^{pv}\right)^2 \end{bmatrix} \tag{59}$$

where σ_t^d and σ_t^{pv} are the standard deviation of forecast error of demand and solar power generation at time t and ρ_t is the correlation factor between random variables. With this definition, (56) can be rewritten in compact form as:

$$\inf_{\mathbb{P}\in\mathcal{D}'} \mathbb{P}\Big(A_t(x)^T\zeta_t \le b_t(x)\Big) \ge 1-\epsilon;\ \forall t\in T \tag{60}$$

where the confidence set $\mathcal{D}'$ is defined as:

$$\mathcal{D}' = \Big\{\mathbb{P}\in\mathcal{M}_+ : \mathbb{E}_{\mathbb{P}}[\zeta_t] = \mu_t = 0, \mathbb{E}_{\mathbb{P}}[\zeta_t{\zeta_t}^T] = \Sigma_t\Big\} \tag{61}$$

The DRCC equation (60) is equivalent to the convex constraint as follow.

$$\sqrt{\frac{1-\epsilon}{\epsilon}}\,\Big\|\Sigma_t^{1/2}A_t(x)\Big\|_2 \le b_t(x);\ \forall t\in T \tag{62}$$

This constraint is derived based on a variant of the Chebyshev inequality. The full proof and description for equivalence were given in [37, 38].

4. Case Study

4.1. Simulation Setup

To assess the effectiveness of the proposed DRCC-based energy management model, the case of an office building with 100 electric vehicle charging piles has been studied. In this work, we consider an office building containing 200 kW installed solar systems and a building battery with capacity of 200 kWh and rated power of 50 kW. These values were selected to have a balance between total demand and generation of the building. The initial SOC level of building batteries is set to be 0.4 and its degradation cost coefficient is considered as 0.35 ¢/kWh [39]. Moreover, the key parameters of EV battery can be found in [19], and it is assumed that the EV owners' target SOC is 100% in order to have the most comfort level. The arrival and departure times of EVs are assumed 7 AM, and 4 PM, respectively, based on a statistical analysis of EV charging behavior in the UK [40]. The other input data associated with EV owners including the initial SOC level at arrival and price requirement for maximum response (λ^{max}) are randomly and uniformly distributed within the range of [0.5,0.6] and [1.5,3.5] ¢/kWh, respectively [25, 40].

In addition, the hourly mean values of solar power generation and demand as well as the hourly price for buying electricity from the main grid are shown in Figure 4, and the FIT rate is assumed 1.5 ¢/kWh less than buying electricity price [25, 35]. Also, to calculate the hourly correlation factor between uncertainties associated with solar power generation and demand, we utilized Denmark historical data in 2019 [35]. The mutual correlation factor and the standard deviation values of uncertainties associated with solar power generation and demand can be found in [41]. Finally, the base charging price of EVs is assumed 6 ¢/kWh, and the confidence level that is determined by the decision maker is set to be $1 - \epsilon = 0.95$.

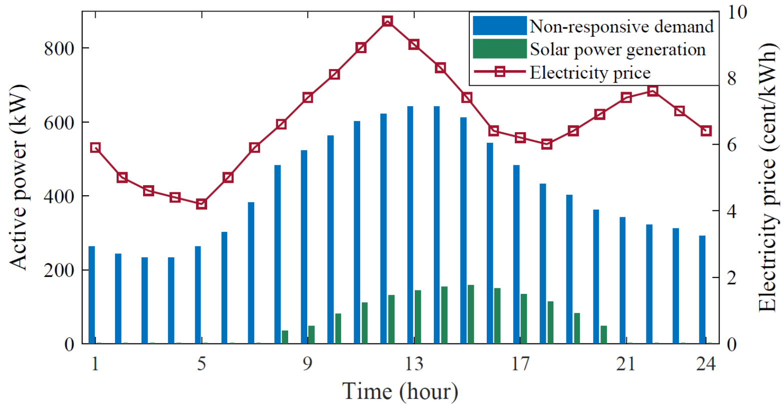

Figure 4: Non-responsive demand and solar power generation (bar chart: left y-axis) and price for buying electricity from the main grid (line plot: right y-axis)

4.2. Numerical Results and Analysis

Considering the parameters and input data mentioned above, we solved the presented DRCC-based building energy management optimization problem. Since the battery plays a key role in the building energy management by peak load shifting, we determine the optimal scheduling of building battery as shown in Figure 5. This figure shows that the building battery is charged during the first few hours of the day when the electricity price is at its minimum level. The charging of battery continues for three hours till the fully charged state is achieved. Then, the battery will remain in the idle mode for six hours till 11:00, and after that when the electricity price increases sufficiently the battery starts to be discharged for three hours, i.e., 11:00-13:00. It is to be noted that the degradation cost of battery in the illustrated optimal scheduling is equal to 1.65$.

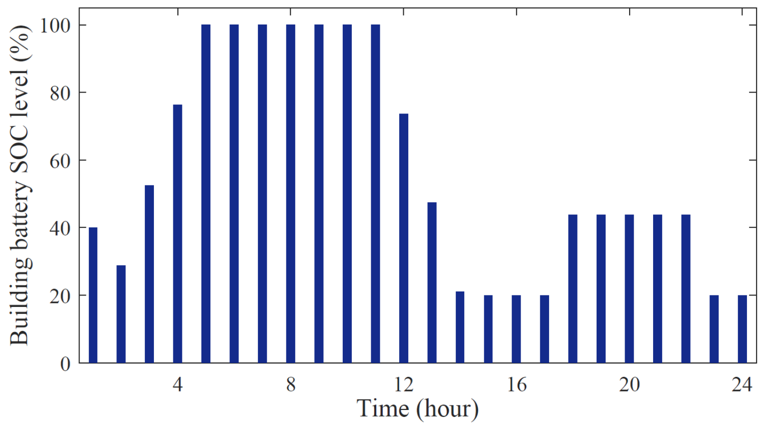

Figure 5: Optimal scheduling of building battery

In the following parts of the simulation study, our proposed model is compared with two other cases: *i*) uncontrolled model where EVs are charged as soon as they are plugged-in, and *ii*) direct control model where the BEMS minimizes the cost of buying electricity from the main grid. Note that in all cases, the EVs will get reimbursed for changing the charging pattern of EV batteries (delaying the charging). Figure 6 depicts the imported electricity from the main grid and charging demand of EVs during plugged-in hours (7:00-16:00). As inferred from this figure, the peak demand in the proposed model has been decreased by 4.4% and 3.6% compared to uncontrolled and direct control models, respectively. Also, this figure illustrates that in the uncontrolled charging case, the EVs are charged as soon as they are plugged-in without considering the electricity price that will put pressure on the network, while the proposed model decreases the charging of EVs during high electricity price hours, i.e., (11:00-13:00). Moreover, in the direct control model, the EVs are charged when the electricity price is low, which makes the minimum cost of importing electricity from the main grid for charging EVs compared to other EV charging models. However, since the direct control model postpones part of charging the EV batteries to the last two hours (15:00-16:00), the BEMS must pay a significant amount of reimbursement to the EV owners. To better illustrate the above discussions, the cost and revenue of BEMS of the office building in the three cases mentioned above are shown in Table 2. As seen in this table,

Table 2: Cost and Revenue of BEMS

	Proposed model	Uncontrolled charging	Direct control
Cost of imported electricity ($)	1020.8	1030.2	1019.6
EV owners' payment for charging ($)	76.3	82.4	60.1
Reimbursement to EV owners ($)	6.1	0.0	22.3
Total operating cost of BEMS ($)	946	949.5	961.2

the reimbursement to EVs in the direct control model is more than that of other cases due to the charging of the EV batteries close to their departure. Also, this table shows that our proposed model has the least total operating cost in comparison to other cases. It is to be noted that the biggest portion of the total operating cost in all cases is related to the cost of importing electricity for supplying non-responsive demand.

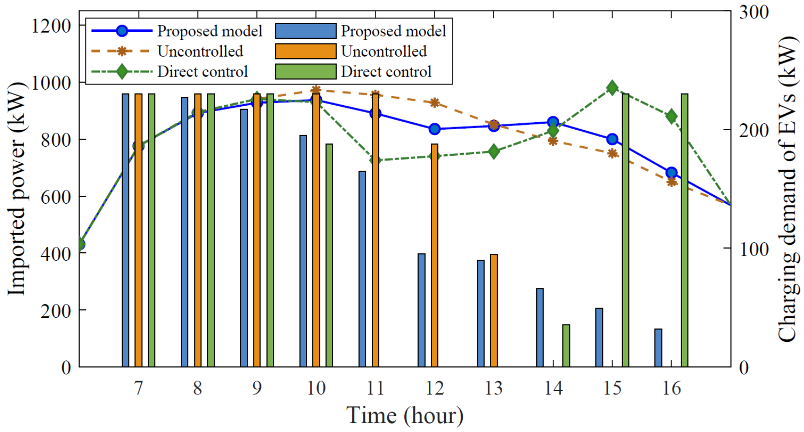

Figure 6: Imported electricity from main grid (line plot: left y-axis) and EVs' charging demand (bar chart: right y-axis)

Moreover, the box plot of transactive market clearing prices and the curve of reduced charging power of EV batteries within plugged-in hours are depicted in Figure 7. As seen in this figure, the clearing price, the decreased charging power of EV batteries, and accordingly, the reimbursement to the EV owners in higher electricity price hours have maximum values. In other words, in this period since the price for buying electricity from the main grid is high, the BEMS employs more of the offered flexibility of EV charging by generating greater clearing prices to convince more EV owners to reduce their charging demand.

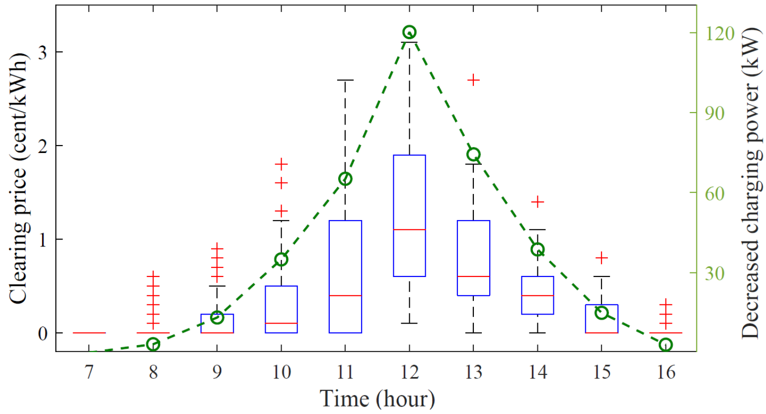

Figure 7: Variations of transactive market clearing price (box plot: left y-axis) and reduced EVs' charging power (line plot: right y-axis)

In addition, the transformer's loss of life factor (*LOL*) for different standard capacities of the distribution transformer in the three cases mentioned above are reported in Table 3. As shown in this table, the transformer aging is significantly accelerated due to the penetration of EVs. For instance, in the case of 630 kVA transformer, penetration of EVs increases the transformer's loss of life factor by at least 5.6 times. Another observation of this table shows that the transformer aging in the proposed model is lower than those of the other two charging models. In this study, the limitation of the transformer's loss of life factor (LoL^{max}) was considered as 0.0137% which is equal to 5% aging per year [42]. Thus, using the proposed method there is no need to change the transformer to meet the LOL limitation for the integration of 100 EVs in this case. However, the direct control and uncontrolled charging approaches necessitate a distribution transformer of greater size. In other words, using these two approaches, we need to replace the 800 kVA transformer with a 1000 kVA transformer, which causes a higher investment cost to the building owner.

Table 3: Transformer's LOL for different capacities of transformer

	630 kVA	800 kVA	1000 kVA
No EVs	0.07313%	0.0029%	0.00028%
Proposed model	0.40793%	0.01196%	0.00086%
Direct control	0.61150%	0.01605%	0.00104%
Uncontrolled	0.70711%	0.01834%	0.00117%

4.3. Sensitivity Analysis

In this section, the impacts of different values of ϵ and correlation factors (ρ) on the cost of BEMS are investigated. For this purpose, first, a sensitivity analysis is carried out to measure the influence of parameter ϵ on the optimal scheduling of building. In this regard, the procurement cost of building with different parameter ϵ, including 0.01, 0.05, 0.1, 0.15, and 0.2 is determined and depicted in Figure 8. As can be seen, the smaller values of ϵ result in the greater value of total cost. In other words, when the value of ϵ decreases, the BEMS will pay more to achieve a more reliable system. Moreover, this figure shows that decreasing the parameter ϵ from 0.05 to 0.01 will increase the procurement cost significantly. Hence, selecting a proper confidence level helps the BEMS to avoid the extremely high cost caused by a strict reliability constraint.

In the second step of sensitivity analysis, we measure the influence of the correlation factor on the optimal solution. The uncertainties of solar power generation and demand might be positively or negatively correlated. For instance, in the area with a high penetration of air conditioning systems for cooling purposes, when the solar radiation and accordingly the solar power generation increases, the demand increases, too. Thus, these uncertain parameters are positively correlated. On the other hand, in the area where the air conditioning systems are utilized in the heating mode, the increase in solar radiation will reduce the demand; and therefore, there is a negative correlation between the uncertainties of solar power generation and demand. In this regard, the procurement cost of building with different values of correlation factor, including $-1, -0.5, 0, 0.5,$ and 1 is shown in Figure 8. As can be inferred from this figure, the negative correlation between uncertainties of solar power generation and demand will increase the total operating cost of building.

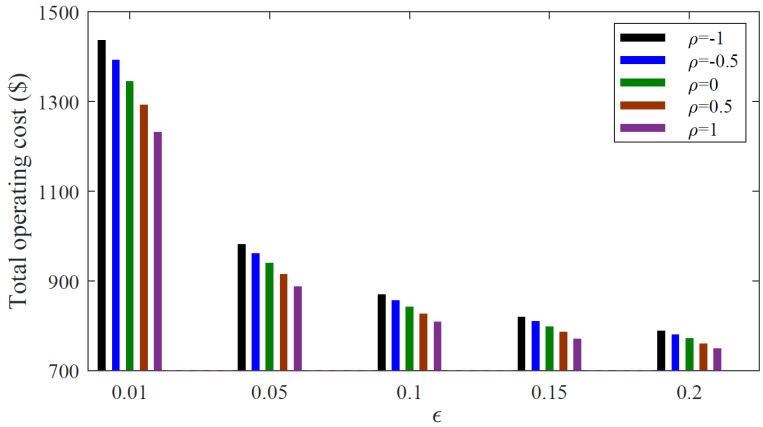

Figure 8: Total operating cost of building with different ϵ and ρ

Table 4: Computational Analysis of the Proposed MILP Model

	Obj. function ($)		Running time (m)	
	MILP	MINLP	MILP	MINLP
# of EVs = 10	928	930	<1	4
# of EVs = 50	937	940	<1	58
# of EVs = 100	948	–	2	–
# of EVs = 150	969	–	7	–

4.4. Computational Performance

In this section, we study the computational performance and solution accuracy of the proposed MILP problem compared to the original MINLP formulation. To attain this goal, the MILP and MINLP optimization problems are respectively solved using CPLEX and BARON solvers on a laptop with the configuration of 16 GB RAM and AMD Ryzen 7 CPU. The running times and the values of objective functions for different numbers of EVs are reported in Table 4. As inferred from this table, the MILP formulation reaches the optimal solution with a lower computation time in comparison to the MINLP model. Also, this table shows that the original MINLP formulation fails to achieve a feasible solution for cases with numbers of EVs 100 and 150. Thus, the linearization procedure that has been performed in this study significantly improves the computational efficiency and the accuracy of the optimal solution.

5. Conclusion

This paper proposed a DRCC-based transactive energy management model to determine the optimal scheduling of an office building considering the uncertainties of solar power generation and demand. To optimally schedule the BEMS of the office building, the flexibility of building batteries and EVs charging were employed. In this regard, to incentivize the EV owners to take part in the energy management program, the BEMS organized a TE market among plugged-in EVs. In the proposed TE market model, the EV owners got reimbursed for the flexibility they offered to the BEMS. To this end, the EV owners individually submitted their response curves and target levels of SOC at departure to the BEMS. Then, the BEMS ran an optimization problem to determine its electricity procurement considering the transactive market among plugged-in EVs. Moreover, due to existing the non-linear equations in the original optimization problem, various linearization techniques were utilized to mitigate the computational burden and extract a more accurate solution. The case of an office building with 100 charging piles was studied to evaluate the effectiveness and applicability of the proposed model. Numerical results illustrated that the proposed model has decreased the cost of BEMS for charging EV batteries (summation of payment for importing electricity and reimbursement to EV owners) by 3.2% and 12.6% compared to uncontrolled and direct control models, respectively. Also, by implementing the proposed model, the EV owners' charging payment has been decreased by 7.4% compared to the uncontrolled charging model. In addition, considering an 800 kVA transformer for the office building, the transformer's loss of life in the proposed building energy management model has been mitigated by 34.8% and 25.5% compared to the other above-mentioned cases.

References

[1] K. G. Firouzjah, A techno-economic energy management strategy for electric vehicles in public parking lot considering multi-scenario simulations, Sustainable Cities and Society 81 (2022) 103845.

[2] V. S. Kasani, D. Tiwari, M. R. Khalghani, S. K. Solanki, J. Solanki, Optimal coordinated charging and routing scheme of electric vehicles in distribution grids: Real grid cases, Sustainable Cities and Society 73 (2021) 103081.

[3] K. N. Qureshi, A. Alhudhaif, G. Jeon, Electric-vehicle energy management and charging scheduling system in sustainable cities and society, Sustainable Cities and Society 71 (2021) 102990.

[4] M. C. Kisacikoglu, F. Erden, N. Erdogan, Distributed control of pev charging based on energy demand forecast, IEEE Transactions on Industrial Informatics 14 (1) (2017) 332–341.

[5] M. H. Mobarak, J. Bauman, Vehicle-directed smart charging strategies to mitigate the effect of long-range ev charging on distribution transformer aging, IEEE Transactions on Transportation Electrification 5 (4) (2019) 1097–1111.

[6] R. Habibifar, A. A. Lekvan, M. Ehsan, A risk-constrained decision support tool for ev aggregators participating in energy and frequency regulation markets, Electric Power Systems Research 185 (2020) 106367.

[7] H. Li, A. Rezvani, J. Hu, K. Ohshima, Optimal day-ahead scheduling of microgrid with hybrid electric vehicles using msfla algorithm considering control strategies, Sustainable Cities and Society 66 (2021) 102681.

[8] Q. Shi, C.-F. Chen, A. Mammoli, F. Li, Estimating the profile of incentive-based demand response (ibdr) by integrating technical models and social-behavioral factors, IEEE Transactions on Smart Grid 11 (1) (2019) 171–183.

[9] S.-W. Park, K.-S. Cho, G. Hoefter, S.-Y. Son, Electric vehicle charging management using location-based incentives for reducing renewable energy curtailment considering the distribution system, Applied Energy 305 (2022) 117680.

[10] L. Gong, W. Cao, K. Liu, J. Zhao, Optimal charging strategy for electric vehicles in residential charging station under dynamic spike pricing policy, Sustainable Cities and Society 63 (2020) 102474.

[11] G. Merhy, A. Nait-Sidi-Moh, N. Moubayed, Control, regulation and optimization of bidirectional energy flows for electric vehicles' charging and discharging, Sustainable Cities and Society 57 (2020) 102129.

[12] K. Kok, S. Widergren, A society of devices: Integrating intelligent distributed resources with transactive energy, IEEE Power and Energy Magazine 14 (3) (2016) 34–45.

[13] M. F. Dynge, P. C. del Granado, N. Hashemipour, M. Korpås, Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations, Applied Energy 301 (2021) 117404.

[14] M. Daneshvar, B. Mohammadi-Ivatloo, S. Asadi, A. Anvari-Moghaddam, M. Rasouli, M. Abapour, G. B. Gharehpetian, Chance-constrained models for transactive energy management of interconnected microgrid clusters, Journal of Cleaner Production 271 (2020) 122177.

[15] A. Mohammad, R. Zamora, T. T. Lie, Transactive energy management of pv-based ev integrated parking lots, IEEE Systems Journal 15 (4) (2020) 5674–5682.

[16] A. Masood, J. Hu, A. Xin, A. R. Sayed, G. Yang, Transactive energy for aggregated electric vehicles to reduce system peak load considering network constraints, IEEE Access 8 (2020) 31519–31529.

[17] L. Affolabi, M. Shahidehpour, W. Gan, M. Yan, B. Chen, S. Pandey, A. Vukojevic, E. A. Paaso, A. Alabdulwahab, A. Abusorrah, Optimal transactive energy trading of electric vehicle charging stations with on-site pv generation in constrained power distribution networks, IEEE Transactions on Smart Grid 13 (2) (2021) 1427–1440.

[18] A. Asrari, M. Ansari, J. Khazaei, P. Fajri, A market framework for decentralized congestion management in smart distribution grids considering collaboration among electric vehicle aggregators, IEEE Transactions on Smart Grid 11 (2) (2019) 1147–1158.

[19] H. Saber, M. Ehsan, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, M. Lehtonen, Network-constrained transactive

coordination for plug-in electric vehicles participation in real-time retail electricity markets, IEEE Transactions on Sustainable Energy 12 (2) (2020) 1439–1448.

[20] M. M. Hoque, M. Khorasany, R. Razzaghi, H. Wang, M. Jalili, Transactive coordination of electric vehicles with voltage control in distribution networks, IEEE Transactions on Sustainable Energy 13 (1) (2021) 391–402.

[21] H. Saber, M. Ehsan, M. Moeini-Aghtaie, H. Ranjbar, M. Lehtonen, A user-friendly transactive coordination model for residential prosumers considering voltage unbalance in distribution networks, IEEE Transactions on Industrial Informatics 18 (9) (2022) 5748–5759.

[22] A. Gadea, M. Marinelli, A. Zecchino, A market framework for enabling electric vehicles flexibility procurement at the distribution level considering grid constraints, in: 2018 Power Systems Computation Conference (PSCC), IEEE, 2018, pp. 1–7.

[23] H. Mazaheri, H. Ranjbar, H. Saber, M. Moeini-Aghtaie, Expansion planning of transmission networks, in: Uncertainties in Modern Power Systems, Elsevier, 2021, pp. 35–56.

[24] Q. Wu, M. Shahidehpour, C. Li, S. Huang, W. Wei, et al., Transactive real-time electric vehicle charging management for commercial buildings with pv on-site generation, IEEE Transactions on Smart Grid 10 (5) (2018) 4939–4950.

[25] H. Saber, H. Ranjbar, S. Fattaheian-Dehkordi, M. Moeini-Aghtaie, M. Ehsan, M. Shahidehpour, Transactive energy management of v2g-capable electric vehicles in residential buildings: An milp approach, IEEE Transactions on Sustainable Energy 13 (3) (2022) 1734–1743.

[26] M. Tostado-Véliz, S. Kamel, H. M. Hasanien, R. A. Turky, F. Jurado, Optimal energy management of cooperative energy communities considering flexible demand, storage and vehicle-to-grid under uncertainties, Sustainable Cities and Society 84 (2022) 104019.

[27] W. Sun, F. Neumann, G. P. Harrison, Robust scheduling of electric vehicle charging in lv distribution networks under uncertainty, IEEE Transactions on Industry Applications 56 (5) (2020) 5785–5795.

[28] H. Golpîra, S. A. R. Khan, A multi-objective risk-based robust optimization approach to energy management in smart residential buildings under combined demand and supply uncertainty, Energy 170 (2019) 1113–1129.

[29] P. Zhao, H. Wu, C. Gu, I. Hernando-Gil, Optimal home energy management under hybrid photovoltaic-storage uncertainty: A distributionally robust chance-constrained approach, IET Renewable Power Generation 13 (11) (2019) 1911–1919.

[30] M. Daneshvar, B. Mohammadi-Ivatloo, M. Abapour, S. Asadi, R. Khanjani, Distributionally robust chance-constrained transactive energy framework for coupled electrical and gas microgrids, IEEE Transactions on Industrial Electronics 68 (1) (2020) 347–357.

[31] Y. Zhou, W. Yu, S. Zhu, B. Yang, J. He, Distributionally robust chance-constrained energy management of an integrated retailer in the multi-energy market, Applied Energy 286 (2021) 116516.

[32] Z. Shi, H. Liang, S. Huang, V. Dinavahi, Distributionally robust chance-constrained energy management for islanded microgrids, IEEE Transactions on Smart Grid 10 (2) (2018) 2234–2244.

[33] IEEE Guide for Loading Mineral Oil Immersed Overhead and Pad Mounted Distribution Transformers.

[34] P. Andrianesis, M. Caramanis, Distribution network marginal costs: Enhanced ac opf including transformer degradation, IEEE Transactions on Smart Grid 11 (5) (2020) 3910–3920.

[35] K. P. Olsen, Hourly time series data of wind and solar power production as well as electricity consumption for all of denmark from the danish tso energinet, Technical University of Denmark (2019).
URL https://doi.org/10.11583/DTU.7599629.v2

[36] O. Ciftci, M. Mehrtash, A. Kargarian, Data-driven nonparametric chance-constrained optimization for microgrid energy management, IEEE Transactions on Industrial Informatics 16 (4) (2019) 2447–2457.

[37] M. R. Wagner, Stochastic 0–1 linear programming under limited distributional information, Operations Research Letters 36 (2) (2008) 150–156.

[38] G. C. Calafiore, L. El Ghaoui, On distributionally robust chance-constrained linear programs, Journal of Optimization Theory and Applications 130 (1) (2006) 1–22.

[39] Y. Guo, C. Zhao, Islanding-aware robust energy management for microgrids, IEEE Transactions on Smart Grid 9 (2) (2016) 1301–1309.

[40] J. Quirós-Tortós, L. F. Ochoa, B. Lees, A statistical analysis of ev charging behavior in the uk, in: 2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM), IEEE, 2015, pp. 445–449.

[41] Input data: Hourly electricity price, fit rate, demand, pv generation, and correlation factor, https://docs.google.com/spreadsheets/d/1CrJvu36KvovIHMN$_{o}XX7Hui4rNuzkbv6/edit?usp = sharingouid = 108196526015412389907rtpof = truesd = true$.

[42] P. Sen, S. Pansuwan, Overloading and loss-of-life assessment guidelines of oil-cooled transformers, in: 2001 Rural Electric Power Conference. Papers Presented at the 45th Annual Conference (Cat. No. 01CH37214), IEEE, 2001, pp. B4–1.