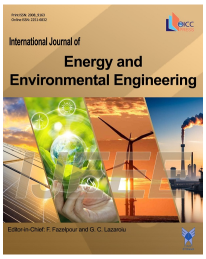

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Transactive Control-Based Optimal Scheduling with Uncertain PV Generation and Demand Response

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Abstract:

Electric vehicles (EVs) are transforming transportation, requiring planned charging networks to handle rising demand, manage power systems, reduce congestion, and integrate renewables. This work develops a stochastic optimization framework for EV charging stations with transactive control to cut carbon emissions and promote EV adoption. Consequently, deploying EVCS will become a crucial strategy for addressing the integration of renewable energy. An innovative approach to supplying electric power stored in EV fleets involves using transportation networks as supplementary infrastructure .The article explores how transportation networks affect EVCS and DR scheduling under uncertain PV output, highlighting the benefits of DR integration for improved efficiency and grid reliability. A mixed-integer linear programming (MILP) model is proposed to enhance the solution quality of the DC power flow method, thereby reducing computational complexity. A detailed evaluation of economic and environmental factors is included, showing a 1.288% overall system cost reduction with EV fleets and DR in scheduling costs, and a 2.431% decrease in EV fleet and solar PV power costs. This research aims to offer a sustainable, cost-effective, and scalable solution for EV charging infrastructure to support future electric mobility, with the dispatching problem verified on a modified IEEE 30-bus system

Keywords: Electric vehicle charging stations; demand response; transactive market; stochastic scheduling; mixed integer linearprogramming

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Nomenclature

Variables:

$CE_{ev_{s,t}}$	Energy capacity of EV fleets ev
$P_{cg_{j,s,t}}, Q_{cg_{j,s,t}}$	Active and reactive power of generation at the unit cg
$PSH_{d,t}$	Shiftable load at time t in the base case
$DeR^{up}_{d,t}, DeR^{dn}_{d,t}$	Scheduled load up and down time at times t
$FE_{ev_{n,s,t}}, TH_{ev_{n,s,t}}$	EV fleet unit $ev$of toll-free and energy-efficient travel plans
$CE_{ev_{s,0}}, CE_{ev_{s,T}}$	Initial/terminal energy storage capacity of the unit EVev
$SR_{cg_{j,s,t}}, SR_{ev_{s,t}}$	Spinning reserve of generation and EV fleet unit cg and ev
$P^{dch}_{ev_{s,t}}, P^{ch}_{ev_{s,t}}$	Discharging/charging power of the EV fleet unit ev
$IH_{ev_{n,s,t}}, IW_{ev_{n,s,t}}$	Binary variable for home and workplace states of the EV fleet unit ev

$IT_{ev_{n,s,t}}$	Binary variable for the travelling states of the EV fleet unit ev
$I^{dch}_{ev_{s,t}}, I^{ch}_{ev_{s,t}}$	Status of charging and discharging of the EV fleet unit ev
$I_{ev_{n,s}}, I^{V2G}_{ev_s}$	Status of travel plan and V2G program of the EV fleet unit ev
$r^{up}_{cg_{j,s,t}}, r^{dn}_{cg_{j,s,t}}$	Up and down regulation of generation at the unit cg
$P^{HO}_{ev_{s,t}}, P^{WP}_{ev_{s,t}}$	Discharging/charging the power of the workplace and home of the unit EV fleet ev
$SOC_{ev_{s,t}}, SOC_{ev_{s,T}}$	Initial/final increment of unit EV fleet ev
$SOC^{dch}_{ev_{s,t}}, SOC^{ch}_{ev_{s,t}}$	Discharging/charging the power of the SOC of the unit EV fleet ev

Indices and Sets:

d, D	Index and set of demand block
t, T	Index and set of time in hours
j, ncg	Index and set of the thermal unit
s, S	Index and set of scenario samples
n	Indices of EV fleet evtravel
m, M	Index of EV fleet evtraffic network connected link
ev, E	Index and set of EV fleets
i, j	Index of network buses

Parameters:

TR_{ev_t}	EV fleet evtravel time t
$CF^{dc,V2G}_{ev}$	EV fleet evdegradation cost with the V2G program
$MADeR_{d,t}$	Maximum adjustable load
$PFD_{d,t}$	Forecasted demand power at the time t
$THC^{fd,V2G}_{ev}$	EV fleet evfixed degradation cost with the V2G program
$RE^{up,\max}_{cg_t}, RE^{dn,\max}_{cg_t}$	Regulation up and down at the unit cg
$CE^{\min}_{ev}, CE^{\max}_{ev}$	Mini/ max energy capacity of EV fleet ev
$CE_{ev_{m,t}}, CT_{ev_{m,t}}$	EV fleet $ev$of energy and toll -free traffic network in time t
CE_{ev_0}, CE_{ev_T}	Initial/terminal stored energy capacity of the unit EV fleet ev
$P^{\min}_{ev}, P^{\max}_{ev}$	Mini/max power of the unit EV fleet ev
π_s	Probability of solar PV scenario samples$s$
PD_{i_t}, SR_t	Total demand and spinning reserve in time t
$Q^{\max}_{cg}, Q^{\min}_{cg}$	Max/min of reactive power generating unit cg
$P^{\max}_{cg}, P^{\min}_{cg}$	Max/min of active power generating unit cg
Z_{ij}	Impedance of the bus i to j
$P^{\max}_{i,j}, P^{\min}_{i,j}$	Max/min network line of bus i to j

1. Introduction

Recently, many countries have been actively developing renewable energy sources (RES), such as wind power and solar photovoltaic (PV), to reduce energy shortages and environmental pollution [1]. RES is being included in the power system at an accelerating rate. Because of its volatility, randomness, and intermittency, renewable energy presents a serious problem for large-scale power system operations. Because wind power output is highly variable, dispatching needs conservative generation schedules, which lowers the efficiency and dependability of operation methods and makes it more difficult to employ RES effectively. However, RES is subject to forecasting errors because weather conditions are difficult to predict accurately [2, 3]. The intermittent and uncertain nature of RES challenges the safe and economical operation of power systems. Additionally, the stochastic scheduling problem becomes more complex with the inclusion of solar PV energy. First, managing the variability of this energy source demands a more flexible power system for high renewable energy integration. Second, in a transactive market setting, the uncertainty of renewable energy creates additional challenges. One of the main drivers for developing new flexible resources is the widespread use of renewable energy. To address the second challenge, a suitable approach that accounts for the uncertainties of solar PV power must be adopted. By employing transactive control and other parameters within a stochastic framework, an electric vehicle (EV) system utilizing transactive control can balance supply and demand. The proposed approach should also consider the importance of EV charging stations and renewable energy sources, along with transactive management.

More reserves are needed to operate power systems safely, addressing the increasing uncertainty of source and load. Because it can temporarily store and release energy generated by RESs, energy storage is a valuable resource. An actual explanation to these challenges involves executing energy storage systems (ESS), which are ideal for integrating RESs. However, the optimal operation of ESS should be conducted at the lowest possible cost to maintain system security within the specified parameters [4, 5]. Various studies have highlighted numerous benefits of integrating ESS into transmission system operations, including reducing variable renewable energy curtailment, alleviating transmission congestion, and improving system resilience [6]. Growing environmental awareness has increased public acceptance of EVs, making them an integral part of modern power systems as an emerging technology. This technology remains a sustainable response to the rising global greenhouse gas and carbon emissions [7]. Electrifying the automotive sector is one of the main ways to achieve sustainable transportation. When EVs become more widespread, greenhouse gas emissions are expected to decrease significantly because of their often-higher efficiency compared to internal combustion engine vehicles. However, a well-developed charging infrastruc-

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ture is essential for successfully integrating EV charging stations (EVCS) into the mainstream transportation network [8]. Using EV fleets in transportation can serve as a storage asset to help address issues related to solar PV generation. Therefore, coordinated scheduling of thermal generation and EVCS must be examined, considering the effects of uncertain solar PV power, reserve markets, and DC network security [9]. This paper presents a comprehensive model for renewable power generation and DC power flow, ensuring accuracy and efficiency within a reasonable time frame. Also, the robustness of the system is enhanced through demand response (DR) programs derived from the proposed approach. Furthermore, the Quasi-Monte Carlo Simulation Method (QMCS) is employed to model the uncertainty in solar PV power generation.

Worldwide clean energy policies are fostering the adoption of low-carbon technologies not only as a means to counteract climate change and balance sustainable economic growth, but also to bring system support benefits and harness the potential of these technologies in the electricity sector. Thus, the traditional network is transitioning with the advent and anticipated increase of clean energy policies and low-carbon technologies such as wind generation, solar power, energy storage systems, and EVs with cost-competitive investments and financial incentives [10]. An important component of expanding renewable output is energy storage, which serves as the vital connection between energy supply and demand chains. However, the stochastic scheduling problem of ESS is challenging to resolve because of the nonlinear link between the change in energy storage level and the charging/discharging power and the coupling constraints of charging/discharging power [11]. ESS is even more important in small-scale isolated power systems where the load demand is more volatile, and the RESs introduce high uncertainty due to a single point of generation as opposed to large power systems with renewable sources, whose aggregation reduces the level of uncertainty. The decision variables can only be based on the uncertain observations up to the present time to address the non-anticipatory in reference [12]. In other words, it means the current decisions must be consistent concerning different uncertainty observations in the future. An example of a representation of the uncertainties is scenario generation, which is based on some distribution assumptions or historical data [13]. The number of scenarios must be low enough to make the formulation workable because the computational complexity rises quickly as the size of the scenario increases. While effective scenario reduction approaches have been proposed [14], accuracy remains an issue due to the small scale of events [15]. A stochastic scheduling model was presented to explain the pricing of electricity reserves in reference [16]. The authors [17] state that modeling of the ramping product and spinning reserve distribution has also been done to handle these uncertainty issues. Researchers have also included uncertain solar PV power in stochastic models for the reserve market [18], but they did not factor in the cost of the market-clearing price. Also, the effects of the energy and reserve markets utilizing stochastic optimization for DC power flow have not been thoroughly studied for the dispatch of thermal generators in combination with the DR program and EVCS in the transportation networks.

Recent studies have integrated EVCS into optimal power system dispatch by constraining DR mechanism response indices to ensure secure operation using various techniques and perspectives [19, 20]. A two-stage EVCS scheduling scheme with solar PV generation and energy storage is proposed in reference [19]. A stochastic dynamic programming method is demonstrated in [20] to account for fluctuations in renewable energy prices, wholesale power price variations, and the uncertainty of EV charging demand. This article discusses EVCS scheduling and the challenges of pricing. As stated in [21], the DR program was employed to ensure optimal operation or scheduling of an IEEE 24-bus system that integrates wind and solar PV with EVCS. However, the uncertainties of PV, the cost of electricity, and their relationship were not considered. The increasing popularity of EVs and the rise of transactive control in the power industry introduce new difficulties for transmission network optimization [22]. It should be emphasized that EVCS operation requires effective integration of demand-side management, especially demand response strategies, to reduce operational costs [23]. The DR program encourages consumers to increase their output profile to lower electricity purchasing costs by utilizing electricity available at a discount during off-peak hours [24]. To implement DR efficiently, the transmission network is connected with large-scale EVs.

Most of the EVCS model research works have already been described; other studies used stochastic problems to determine the best time to schedule EVCS in the network of transportation for energy [25]. The network-constrained unit commitment (NCUC) issue with electric vehicles and PV penetration is covered [26]. A stochastic problem is used to evaluate the techno-economic viability of various facilities, such as conveying roadways, railway lines, and transportable energy storage [27]. The coordinated planning of transportation and electric power networks enhances grid stability, reduces congestion, and improves the integration of electric vehicles and renewable energy [28]. The implications of the EVCS in coupled traffic electric networks are studied to minimize operational costs overall, reduce traffic congestion, and improve wind energy integration [12]. A solution for the stochastic problem in electric traffic networks with thermal units and transportation traffic model difficulties. However, there wasn't much mention of the transportation network in the literature [29]. A two-stage stochastic model to manage the PV uncertainty, considering transportable EVCS to enable flexibility in the transmission system [30]. In addition, flexible EV charging techniques would increase the efficiency of the DR programs and the transportation infrastructure. Most present models are created from a transmission grid perspective, and few of them fully incorporate crucial factors such as the DR program of both EV fleets and consumers. The DR programs are responsible for changing energy use in response to shifts in power prices at some time interval [31]. DR programs are considered when scheduling power systems to reduce costs and peak loads. The impact of the DR program, considering three distinct forms of demand, is evaluated in the operation scheduling problem with solar power penetration [32]. For efficient scheduling with an incentive-based DR program for distributed generation has provided a stochastic model that lowers the cost of generators and transmitted electricity while increasing DR profit [33]. The above-mentioned studies have ignored the coordinated scheduling of EVCS in the transportation network and DR programs based on transactive control.

The increased deployment of energy resources like solar panels and energy storage systems, as well as the integration of EVs with transactive energy management, is receiving more attention. An EVCS housed inside office buildings with rooftop PVs uses a dynamic pricing system to establish transactive control rates for trading energy among EVs [34]. Two market models were included in this work's transactive energy outline: a decentralized real-time market and an hourly ahead market with system operation constraints that take into account the DC power flow network model. Using a predetermined power purchase market, [35] integrates the optimal scheduling of privately owned EVCSs into a transactive market framework between EVCSs and a remote PV farm. When it comes to transactive energy operations based on power charging and discharging, whether it be in parking lots or EV charging stations, the works in [36] EVs directly participate. [37] describes a market-based network of EV charging stations in which EVs employ transactive energy management. Moreover, [38] proposed an optimization problem for the transmission system's transactive energy management system incorporating stochastic scheduling using mixed integer linear programming (MILP). Existing studies have examined EVCS investment costs with transactive control using DC network security from different aspects by applying various techniques. None of the research referenced in the literature examined the relationship between uncertain solar PV, DR programs, and electricity pricing while addressing the optimal problem of EVCS via fleets in power networks.

When addressing a stochastic scheduling problem with EV charging stations for transactive energy management, the authors are unaware of any comprehensive model that considers uncertain wind. To highlight the benefits and contributions of this work, a comparison with similar studies is shown in Table 1. In summary, existing research reveals the following insights gaps:

- Existing research has made significant progress in addressing DC power flow network constraints for thermal units in the deterministic and stochastic problem [11, 13, 14, 15, 19, 20, 21, 25], but none of the reviewed works consider the EV charging stations as flexible options with high solar PV penetration on the stochastic scheduling problem of the electrical system.
- Several studies consider both renewable and non-renewable generating units. However, flexible sources like demand response, solar PV, and EVCS should be added to the power system to enhance network operation and security. Nonetheless, the references [28, 12, 29, 30, 35, 36, 38] do not account for DR programs or transactive energy management in EV transportation networks.

To address the research gaps mentioned above, this paper proposes a strategic EVCS operation framework that incorporates DR programs and renewable generation, based on transactive control. The Quasi-Monte Carlo Simulation (QMCS) method for hourly solar PV power produces a series of scenarios that represent the uncertainty modeling of solar PV output. The proposed K-means clustering method is used for scenario reduction through a backward reduction approach. This approach provides an hourly schedule for charging and discharging the EV fleet, along with the optimal dispatch of thermal units, PV curtailment, and DR programs, while maintaining network constraints. Therefore, this work formulates an operational problem that considers system operation, including solar PV generation and grid-connected EVs. In summary, the paper aims to analyze network transportation using EVCS and DR programs based on transactive mechanisms within a stochastic scheduling framework. The contributions of this paper are threefold:

1. Proposes a two-stage stochastic scheduling considering transportation networks for EVCS, DC network constraints, and DR programs to alleviate traffic congestion and improve power grid economics in the transactive mechanism.
2. To develop a probabilistic optimization framework based on the QMCS method to make various scenarios that minimize grid operation and carbon emissions in an uncertain environment.
3. Utilizing the DR program to control solar power variability, smooth the load profile, lower operating costs, and reduce gas emissions.

The rest of this paper is organized as follows: Section 2 provides a detailed model of renewable power generation. Section 3 gives the mathematical expressions of the stochastic optimal operation model of the EVCS and the DR program. Solution methodologies are presented in Section 4. Numerical simulation results are reported and discussed in Section 5. Section 6 concludes this study.

1.1 Experimental analysis of Uncertainty

This paper employs a two-stage stochastic programming approach to investigate the relationship between electricity market pricing and system flexibility. Safety and

Table 1. Comparison of this paper with similar works on EVCS operation

References	DR program	Solving methods	Power flow		Uncertainty		Reservet market	EVCS
			DC	AC	Wind	PV		
[11]	-	CPLEX	-	-	✓	-	-	-
[13]	-	MILP	-	-	✓	-	-	-
[18]	-	CPLEX	✓	-	-	✓	✓	-
[21]	✓	CPLEX	✓	-	✓	-	-	-
[23]	✓	MINLP	-	✓	✓	-	-	✓
[26]	-	MILP	✓	-	-	✓	-	✓
[28]	✓	Benders	✓	-	✓	-	-	✓
[29]	✓	MINLP	-	✓	✓	✓	✓	✓
[30]	✓	MILP	✓	-	-	✓	✓	✓
[32]	✓	CPLEX	✓	-	✓	-	✓	-
[33]	✓	Two-layer	✓	-	-	✓	✓	-
[34]	✓	MINLP	-	✓	-	✓	-	✓
[35]	-	MIQCP	-	✓	-	✓	✓	✓
[37]	-	MILP	✓	-	-	✓	✓	✓
Current paper	✓	MILP	✓	-	-	✓	✓	✓

economy can be balanced by varying the degree of confidence. This section presents probabilistic modeling for PV power generation units, traditional generators, and electricity prices.

1.2 Distribution of PV Generation Probabilities

PV generation is largely dependent on solar irradiation, and its power injection P_{PV} probability function (PDF) can be assumed as proportional to the irradiation (s) with a unitary power factor, as shown in (1). $P_{PV_{rated}}$represents installed PV power capacity and $f_\beta(s)$ represents the probability density function of solar irradiation. This irradiation s can be modeled using the Beta distribution as expressed in (2) [18,24].

$$P_{PV} = P_{PV_{rated}} S \tag{1}$$

$$f_\beta(s) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} S^{(\alpha-1)}(1-S)^{(\beta-1)} \tag{2}$$

Where $\Gamma(.)$ is the gamma function and the parameter α and β are calculated in terms of the solar irradiation expected value μ_s and standard deviation $\sigma_s$using (3) and (4).

$$\alpha = \mu_s^2(1-\mu_s)/\sigma_s^2 - \mu_s \tag{3}$$

$$\beta = \alpha(1-\mu_s)/\mu_s \tag{4}$$

1.3 Electricity Prices

The normal distribution $f(C_g)$for a certain mean $\mu_{CE}$and standard deviation σ_{CE}taken from a historical record as a reference [27] is used to model the uncertainty of power prices C_E.

$$f(C_g) = \frac{1}{\sqrt{2\pi}\sigma_{C_E}} \exp\left(-\frac{(C_E-\mu_{C_E})}{2\sigma_{C_E}^2}\right) \tag{5}$$

1.4 Traditional Generators

Considering the value-point impact, the conventional generator's fuel cost function can be represented as follows:

$$C\left(P_{cg_j}\right) = a_j + b_j P_{cg_j} + c_j P_{cg_j}^2 \tag{6}$$

Where $C\left(P_{cg_j}\right)$ [28], is the fuel cost function for each traditional unit$i$, a_j , b_j, c_j are the fuel cost coefficients of each traditional unit. Monte Carlo simulation (MCS) is the most effective tool to be utilized to study the probabilistic nature of a large complex system that includes multiple input stochastic variables, such as solar PV power and electricity prices. However, MCS should generate thousands of samples for each random variable to accurately track the real output variables for the system operation of the proposed work. In this research, MCS utilized quasi-sampling QMCS, which allows the MCS to converge faster with such an accurate tracking ability. Using their respective probability functions, the likelihood of each value of the uncertainty parameters is computed. Finally, this paper proposed a K-means clustering algorithm [39] to reduce the number of scenarios, as well as provide information on various scenario generation and reduction strategies.

2. Problem Formulation

While the latter primarily arises from the presence of the inherent randomness and volatility of RES output. To maintain real-time power balance within the system in an uncertain environment, adjustments to the thermal power unit, EV fleet, and network security procured from the main grid are necessary. Therefore, the real-time power balancing cost comprises the adjustment cost of thermal power unit output, EV charging costs cost and reserve cost scheduling. This proposed optimization problem considers the correlation between random input factors, such as solar PV and electricity prices, to determine the optimal locations, power ratings, and charging/discharging schedules for each EV fleet to ensure proper system operation. The objective

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function is equivalent to minimizing market operating costs, as shown in Equation (7).

$$\begin{aligned}\min \quad & \sum_{t\in T}\sum_{s\in S}\pi_s\left(\sum_{j\in ncg}\left(C(P_{cg_{j,s,t}})+RE^{up}_{cg_t}r^{up}_{cg_{j,s,t}}\right.\right.\\ & \left.\left.+RE^{dn}_{cg_t}r^{dn}_{cg_{j,s,t}}\right)\right)\\ & +\left(\sum_{s\in S}\pi_s\left(\sum_{ev\in E}I^{V2G}_{ev_s}THC^{fd,V2G}_{ev}\right.\right.\\ & \left(\sum_{t\in T}\sum_{ev\in E}\left(IT_{ev_{n,s,t}}TH_{ev_{n,s,t}}\right)\right.\\ & \left.\left.\left.+\left(CF^{dc,V2G}_{ev}P^{dch}_{ev_{s,t}}\right)I^{dch}_{ev_{s,t}}\right)\right)\right)\end{aligned} \tag{7}$$

2.1 Constraints of EVCS

These constraints are based on the likely values of uncertainty parameters and include constraints and equations for the network, thermal units, RESs, DR programs, and EV fleets. Although the EV fleets produce hourly scheduled states, the system can be complex because EV fleets are connected to the grid at work or home. EV fleets are represented by binary variables, as shown in equations (8)-(9), indicating whether they are at work, home, or on the road. The connected links of a specific commuter route can be used to model the energy levels and toll-free continuous states described in constraints (10-20). These links mimic the energy and toll-free states shown in constraints (10) and (11). Additionally, the grid acts as a storage system for the EV fleet, representing V2G input. EV fleets also have defined minimum and maximum energy capacities. Therefore, the various transportation constraints include:

$$\sum_{t\in Hto\,W} IT_{ev_{n,s,t}} \geq TR_{ev_t}, \quad \forall s,\forall ev,\forall n \tag{8}$$

$$\sum_{t\in WtoP} IT_{ev_{n,s,t}} \geq TR_{ev_t} \quad \forall s,\forall ev,\forall n \tag{9}$$

$$FE_{ev_{n,s,t}} = \sum_{m\in M}\zeta_{ev_{m,s,t}}CE_{ev_{m,t}} \quad \forall s,\forall ev,\forall n \tag{10}$$

$$TH_{ev_{n,s,t}} = \sum_{m\in M}\zeta_{ev_{m,s,t}}CT_{ev_{m,t}} \quad \forall s,\forall ev,\forall n \tag{11}$$

$$IH_{ev_{n,s,t}}+IW_{ev_{n,s,t}}+IT_{ev_{n,s,t}} = 1, \ \forall s,\forall n,\forall ev,\forall t \tag{12}$$

$$I^{dch}_{ev_{s,t}}+I^{ch}_{ev_{s,t}} \leq IH_{ev_{n,s,t}}+IW_{ev_{n,s,t}}, \ \forall s,\forall ev,\forall n \tag{13}$$

$$I^{dch}_{ev_{s,t}} \leq I^{V2G}_{ev_s}, \ \forall s,\forall ev,\forall t \tag{14}$$

$$\sum_{n\in TS_e} I_{ev_{n,s}} = 1, \quad \forall ev,\forall s \tag{15}$$

$$\begin{aligned}P^{\min}_{ev}\sum_{n\in TS_e} I_{ev_{n,s}}IH_{ev_{n,s,t}} &\leq P^{HO}_{ev_{s,t}}\\ &\leq P^{\max}_{ev}\sum_{n\in TS_e} I_{ev_{n,s}}IH_{ev_{n,s,t}}, \ \forall s,\forall ev,\forall t\end{aligned} \tag{16}$$

$$\begin{aligned}P^{\min}_{ev}\sum_{n\in TS_e} I_{ev_{n,s}}IW_{ev_{n,s,t}} &\leq P^{WP}_{ev_{s,t}}\\ &\leq P^{\max}_{ev}\sum_{n\in TS_e} I_{ev_{n,s}}IW_{ev_{n,s,t}}, \ \forall s,\forall ev,\forall t\end{aligned} \tag{17}$$

$$P^{HO}_{ev_{s,t}}+P^{WP}_{ev_{s,t}} = P^{ch}_{ev_{s,t}}-P^{dch}_{ev_{s,t}}, \ \forall s,\forall ev,\forall t \tag{18}$$

$$\begin{aligned}& I^{ch}_{ev_{s,t}}+I^{dch}_{ev_{s,t}}\\ & \leq \sum_{n\in TS_{ev,t}} I_{ev_{n,s}}\left(IH_{ev_{n,s,t}}+IW_{ev_{n,s,t}}\right), \forall s,\forall ev,\forall t\end{aligned} \tag{19}$$

$$CE^{\min}_{ev} \leq CE_{ev_{s,t}} \leq CE^{\max}_{ev}, \ \forall s,\forall ev,\forall t \tag{20}$$

Constraint (12) depicts the EV fleet as a single state at each hour; Constraint (13) shows that the EV fleet contributes to the grid by sharing electricity from homes or workplaces; and Constraint (14) shows that EV fleets supply power to the grid while they are engaged in V2G mode. The EV fleet's trip plan state, or binary status, is represented by constraint (15). The inequality restrictions on power exchange between the grid and EV fleet are provided by constraints (**??**)-(17), which consider the charging/discharging rates and the fleet's current conditions. Electricity exchange between the house, office, and the grid, similar to charging and discharging electricity at each solar PV scenario, is shown by constraint (18). According to the travel plan, constraint (19) depicts the condition of the EV fleet, which can only be charged or discharged while parked. Constraints (21) and (22) specify the initial and terminal energy requirements, while constraint (20) defines the maximum and minimum capacity of EV fleets. Constraint (24) provides the battery's state of charge (SOC), which is the sum of the SOC during transport, charging, and discharging modes, and constraint (23) shows the battery energy balance. Constraints (25) and (26) use a linear function of charging and discharging power to approximate the SOC. The initial energy value of each EV fleet, the charging/discharging capacity, and the SOC must all be recalculated continuously at specific procedure stages.

$$CE_{ev_{s,0}} = CE_{ev_0} \quad \forall s,\forall ev,\forall t \tag{21}$$

$$CE_{ev_{s,T}} = CE_{ev_T} \quad \forall s,\forall ev,\forall t \tag{22}$$

$$CE_{ev_{s,t+1}} = CE_{ev_{s,t}}+SOC_{ev_{s,t}} \quad \forall s,\forall ev,\forall t \tag{23}$$

$$SOC_{ev_{s,t}} = SOC^{ch}_{ev_{s,t}}-SOC^{dch}_{ev_{s,t}}-SOC^{T}_{ev_{s,t}}, \forall s,\forall ev,\forall t \tag{24}$$

$$0 \leq P^{dch}_{ev_{s,t}} \leq P^{\max}_{ev}I^{dch}_{ev_{s,t}}, \ \forall s,\forall ev,\forall t \tag{25}$$

$$0 \leq P^{ch}_{ev_{s,t}} \leq P^{\max}_{ev}I^{ch}_{ev_{s,t}}, \ \forall s,\forall ev,\forall t \tag{26}$$

2.2 Generation and network constraints

The power generation of each unit must be limited between the minimum and maximum generation output of active and reactive power, as shown in equations (27) and (28). The sum of the powers generated by the thermal, solar PVs and EV fleets charging/discharging should be equal to the load demand in each sample scenario as specified by equation (29). Equations (30) and

(31) show the DC security and network line flow limits for solar PV power samples, respectively. The following are the subject technical constraints for each period in every sample:

$$P_{cg_j}^{\min} \le P_{cg_{j,s,t}} \le P_{cg_j}^{\max}, \ \forall s, \forall t \tag{27}$$

$$Q_{cg_j}^{\min} \le Q_{cg_{j,s,t}} \le Q_{cg_j}^{\max}, \ \forall s, \forall t \tag{28}$$

$$\sum_{j \in ncg} P_{cg_{j,s,t}} + \sum_{j \in npvg} P_{pvg_{j,s,t}} + \sum_{i \in Bus} \sum_{ev \in E} \left(P_{ev_{s,t}}^{dch} - P_{ev_{s,t}}^{ch} \right) = \sum_{i \in nl} PD_{i_t} \ \forall s, \forall t \tag{29}$$

$$-P_{i,j}^{\min} \le P_{i,j,s,t} \le P_{i,j}^{\max}, \ \ \forall t, \forall s \tag{30}$$

$$P_{i,j,s,t} = \frac{\phi_{s,i,t} - \phi_{s,j,t}}{Z_{i,j}}, \ \ \forall t, \forall s \tag{31}$$

2.3 DR program model

The action taken by certain users to reduce or modify their power demand in response to an external signal is known as DR programs. Demand-side response is essentially used to adjust energy demand so that it aligns with the power system's capacity.

In essence, these load response initiatives focus on regulating demand rather than adjusting supply [27, 31]. The demand response's overall power is expressed as a constraint (32) and (33). In addition, as stated in (34), there must be no net shifting of demand during the allocated period, and constraints (35) and (36) provide hourly variable load limits.

$$PDeR_{d,t} = PFD_{d,t} + PSH_{d,t} \tag{32}$$

$$PSH_{d,t} = (DeR_{d,s,t}^{up} - DeR_{d,s,t}^{dn})PFD_{d,t} \tag{33}$$

$$\sum_{t \in T} PSH_{d,t} = 0 \tag{34}$$

$$0 \le DeR_{d,s,t}^{up} \le MADeR_{d.t} \tag{35}$$

$$0 \le DeR_{d,s,t}^{dn} \le MADeR_{d,t} \tag{36}$$

2.4 Reserve and regulation constraints

The proposed stochastic model considers the reserve of thermal and EV transportation units, with reserve constraints expressed as (37) in all scenario samples. Moreover, the thermal reserve regulation of active power is determined by (38), respectively. Finally, constraints (39) and (40) regulate up and down outline the requirements for spinning reserves.

$$\sum_{ncg \in j} SR_{cg_{j,s,t}} + \sum_{ev \in E} SR_{ev_{s,t}} \ge SR_t, \qquad \forall s, \forall t \tag{37}$$

$$P_{cg_{j,s,t}} = r_{cg_{j,s,t}}^{up} - r_{cg_{j,s,t}}^{dn} \tag{38}$$

$$RE_{cg_t}^{up,\max} \ge r_{cg_{j,s,t}}^{up} \tag{39}$$

$$RE_{cg_t}^{dn,\max} \ge r_{cg_{j,s,t}}^{dn} \tag{40}$$

2.5 The Proposed Methodology

A two-stage stochastic scheduling problem is employed to solve the objective function (Equation(7)), using a CPLEX solver [40, 41] and an optimization approach to solve the stochastic problem with EVs and DR program. The proposed model determines the charging and discharging performance of each EV fleet using the starting grid data, as described in constraints (25) and (26). Based on market power pricing and battery capacity, all EV fleets are routed to the closest arrival time. Parking lots are given the EV scheduling challenge only when the requirements are satisfied. Last but not least, every EV fleet has a 24-hour transactive control DR program with an optimal generation dispatch. As indicated in the proposed model, use the initial grid data to establish each EV fleet's charging and discharging performance, as outlined in constraints (25) and (26). All EV fleets are directed to the nearest arrival time based on battery capacity and market power prices. The EV scheduling problem is assigned to parking lots only if the constraints are met. Finally, each EV fleet has an optimized generation dispatch with a DR program based on transactive control for 24 hours. This study employs a two-stage stochastic scheduling approach with solar PV power to optimize day-ahead EV fleet dispatch, thereby minimizing operating costs while adhering to system constraints. It introduces energy transporters and employs a transactive management-based solution for EV fleets, solar PV power, and DR program, as shown in Figure 1. The following steps could be considered the optimization method for the proposed model as follows:

- Step 1 (Input Parameter): The relevant parameters, such as generation data, solar PV power data, transmission line data, EV fleet data, and forecasted load demand data. Also, EV movement data, charging demand, road networks, and grid constraints are analyzed.

- Step 2 (Scenario generation and reduction technique): Typical cases are selected using the QMCS method. The K-Means algorithm groups locations based on demand intensity, ensuring minimal travel distance for EV users. This step refines the optimization process by focusing on the most critical scenarios, improving computational efficiency.

- Step 3 (Deterministic optimization): The first stage problem is solved by determining the optimal operation of EV fleets while minimizing overall cost and managing their charging and discharging performance over 24 hours. This step considers various constraints, including EV fleet limitations, transmission line flow limits, and smooth load profiles, ensuring an efficient and balanced system operation.

- Step 4 (Stochastic optimization): Determining the stochastic operation of solar PV scenarios, samples with EV fleets, and the DR program while reducing

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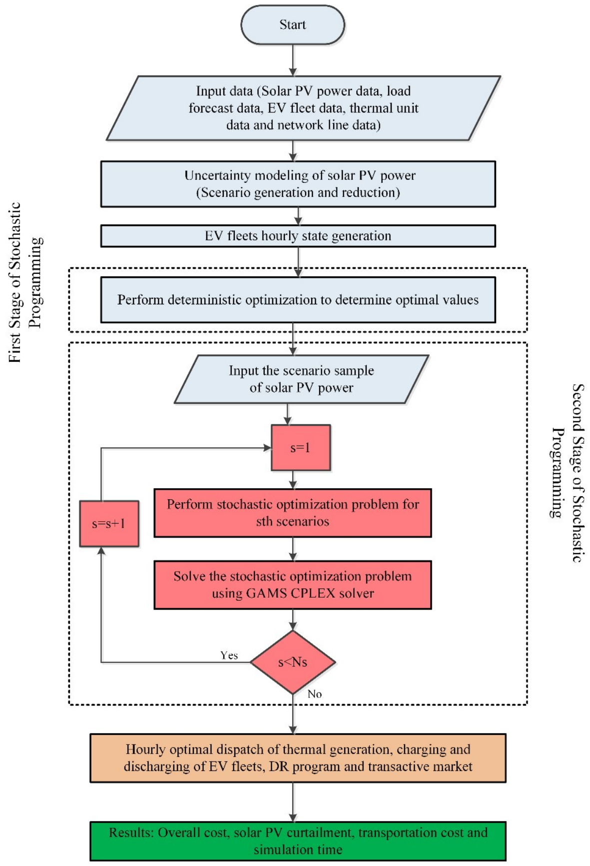

Figure 1. Proposed Algorithms

overall cost and controlling their charging and discharging behavior over 24 hours solves the second stage problem.

- Step 5 (Final stage): Involves executing the charge/discharge technique to achieve cost reduction. The predicted outcomes include optimal charging and discharging rates, total operational costs, wind power curtailment, and the overall solution time. This structured approach ensures an effective balance between cost efficiency and system stability in the integration of EV fleets and renewable energy sources

2.6 Optimization Process

Monte Carlo simulation (MCS) is the most effective technique for analyzing the stochastic features of a large complex system with numerous inputs and stochastic variables, such as solar power, load power, and electricity price. However, MCS needs to generate hundreds of samples for each random variable in order to accurately track the actual output variables for the power system that is being studied. The quasi-sampling (QMCS) used by the MCS in this work allows the MCS to converge faster while retaining a high level of tracking accuracy. Additionally, MCS is combined with Cholesky decomposition to preserve the actual correlation matrix between the input random variables. The following steps can be regarded as the optimization process for the proposed model:

1: Generate Initial Scenarios Using QMCS

1.1. Initialize a low-discrepancy sequence generator in d dimensions:
QMC = Initialize QMC Sequence(d)

1.2. Generate N quasi-random samples:
For $i = 1$ to N:
u_i = QMC. Next () // $u_i \in [0, 1]^d$

1.3. Map to target distribution using inverse transform or sampling method:
For $i = 1$ to N:
$s_i = F^{-1}(u_i)$

1.4. Store the scenario set:
$S = \{s, \ldots, s_N\}$

2: Reduce Scenarios Using K-means Clustering

2.1. Initialize K cluster centroids (e.g., using K-means++):
$\{c, \ldots, c_K\} \leftarrow$ randomly selected from S

2.2. Repeat until convergence:

a. Assignment Step:
For each scenario $s_i \in S$:
Assign s_i to nearest centroid c_j

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b. Update Step:
For each cluster j:
$c\_j \leftarrow$ mean of all s_i assigned to cluster j

2.3. After convergence: For each cluster j:
$r_j = c_j$ // Reduced scenario = centroid
w_j = (# of $_i$ in cluster j) / N //
Weight = proportion of original scenarios

3: Output

Return:

- Reduced scenario set $R = \{r, ..., r_K\}$
- Associated weights $W = \{w, ..., w_K\}$

2.7 Result and Discussion

To demonstrate the advantages of the proposed optimization strategy for EVs in transmission networks is tested by a solar PV power integrated model and DR programs are tested, and network scheduling cases based on transactive control will be discussed in this section. The proposed stochastic optimization tool, considering solar PV power and DR programs, is simulated using the CPLEX solver and GAMS software on modified IEEE 30-bus test networks. The stochastic model takes into account DC network security when coordinating EV charging stations with renewable energy sources and DR programs. Using the suggested research framework, the model considers an MILP problem, as illustrated in Figure 2.

2.8 Case Study

The modified IEEE 30-bus system is taken from a reference [42] and includes nine thermal units, two solar PV farm-RES, and 41 network lines. The highest load of the generator is 386 MW, while its total installed volume is 470 MW. Assume that the network line connects two cities, orange and green, as depicted in Figure 3. Also, two solar PV farms with a combined capacity of 75 MW at bus 23 (green city) and 100 MW at bus 1 (orange city). Figure 4 shows each city's EV fleets and traffic network structure. Also, the hourly energy price cost is 18$, 28$, and 35$. Throughout this work, it is assumed that all loads can participate in DR programs with a maximum rate of 0.3. Figure 5 displays the hourly load profile data.

According to expected traffic patterns, 4,500 EVs will be divided over four fleets. It displays several EV fleets from two cities; for instance, OF1-OF4 displays four various EV fleets from the city of Orange and Green. Table 2 also displays the maximum and lowest capacities of each city fleet, as well as the maximum exchange power of each fleet. It next displays the network home node and the associated node of the EV fleet, followed by the workplace network and the corresponding EV fleet node. The mapping between the traffic network and power grid buses is shown in Table 3. The minimum capacity is specified at 20% of the battery capacity, and the cost of the battery is fixed at $20 per car per year and $10 per MWh [43]. Also, the parameters of travel characteristics of the EV fleets are listed in Table 4. It is assumed that the driving energy needed to travel one way is the same as getting back to the starting point.

Wind uncertainties are modeled using scenario generation and reduction, with 1000 scenarios based on the QMCS technique [40]. However, the large number of potential scenarios imposes a significant computational problem. Then, a k-means clustering technique reduction base is used to reduce the number of scenarios for each parameter to 10.

2.9 Result Analysis

To demonstrate the effectiveness of the two-stage stochastic dispatching model, this case study is performed on an IEEE 30-bus system. A system is used to apply the proposed strategy and assess the impact of optimizing EV fleets with the DR program on system operation. The following three cases are used in this section to examine the flexibility of resources:

1) Case 1: Deterministic with thermal and solar PV power.
2) Case 2: Stochastic with EV fleets and solar PV power.
3) Case 3: Stochastic with EV fleets, PV, and DR program.

2.10 Case 1: Deterministic with thermal and solar PV power

This section evaluates the impact of integrating generating units and solar PV on system operating costs. Figure 6 shows that coordinating the schedule of generating units with solar PV power optimizes energy use, reducing overall energy consumption while also saving energy. Thermal units G1, G2, G5, and G9 are dispatched for the entire 24-hour period. This saved energy will be used in the upcoming hours when the system load is high. When demand increases, the stored energy will be consumed accordingly. Since Bus 1 has the most affordable solar PV power and grid units, the system is designed to draw the majority of its electricity from it. However, as shown in Figure 6, units G3, G6, and G7 are scheduled between 4–12 hours, while units G4 and G8 are scheduled from 13–24 hours. As a result, the system has not fully utilized the grid operation provided by heat unit 1 and solar PV power. Units G7 and G8 will therefore be dispatched between 12 and 22 hours. With a solar PV farm, the total system operation cost is $ 201,322.76, which is less than the $ 225,424.87 cost without solar PV electricity.

2.11 Case 2: Stochastic with EV fleets and solar PV power

The thermal and electric vehicle transportation in stochastic problems with solar PV power is shown in Figure 7. The benefits of establishing 100% EV fleets are explained in this case study. For 24 hours, the initial units G1, G5, and G9 are always scheduled. Units G2,

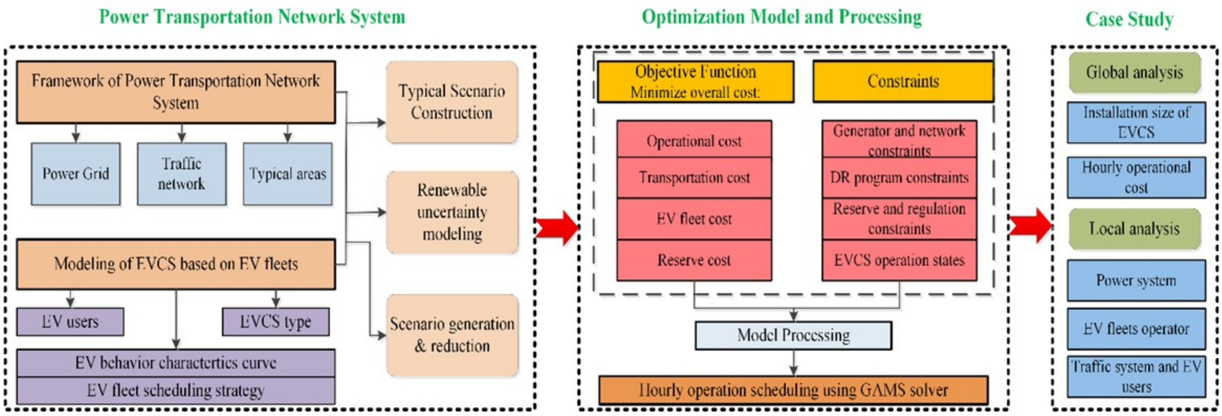

Figure 2. Framework of the proposed research

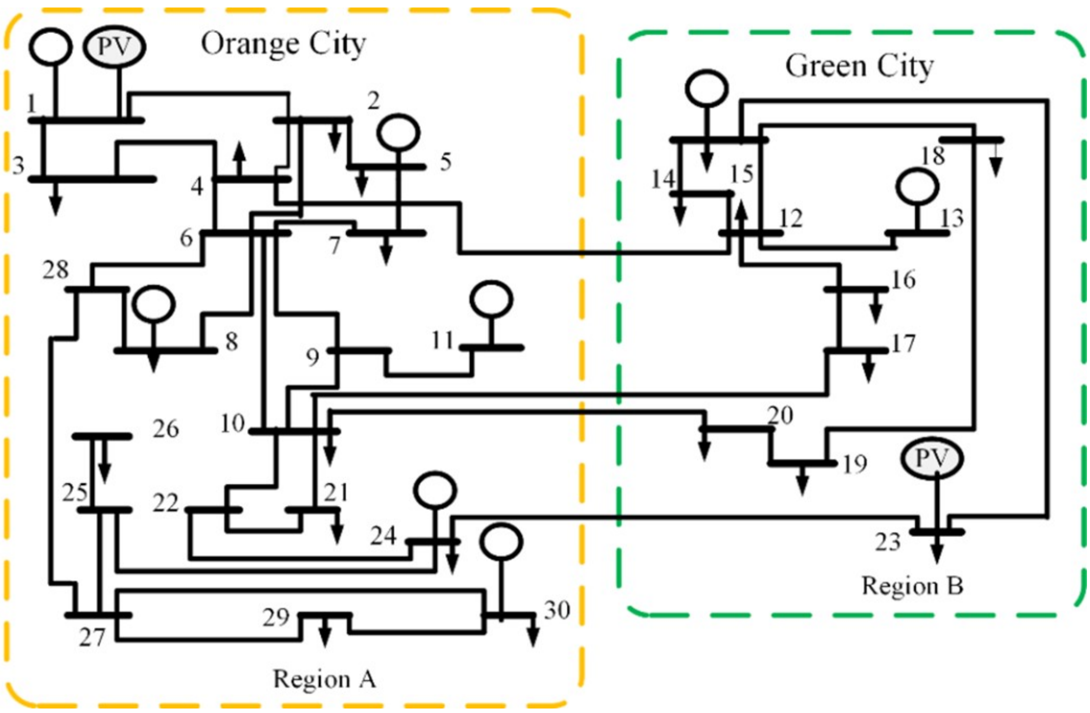

Figure 3. Network power in the IEEE 30-bus system

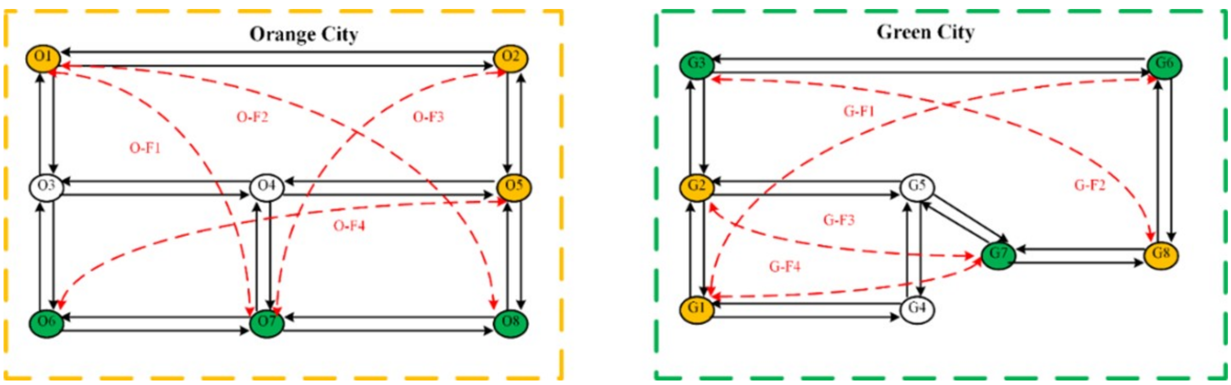

Figure 4. EV traffic network in the IEEE 30-bus system

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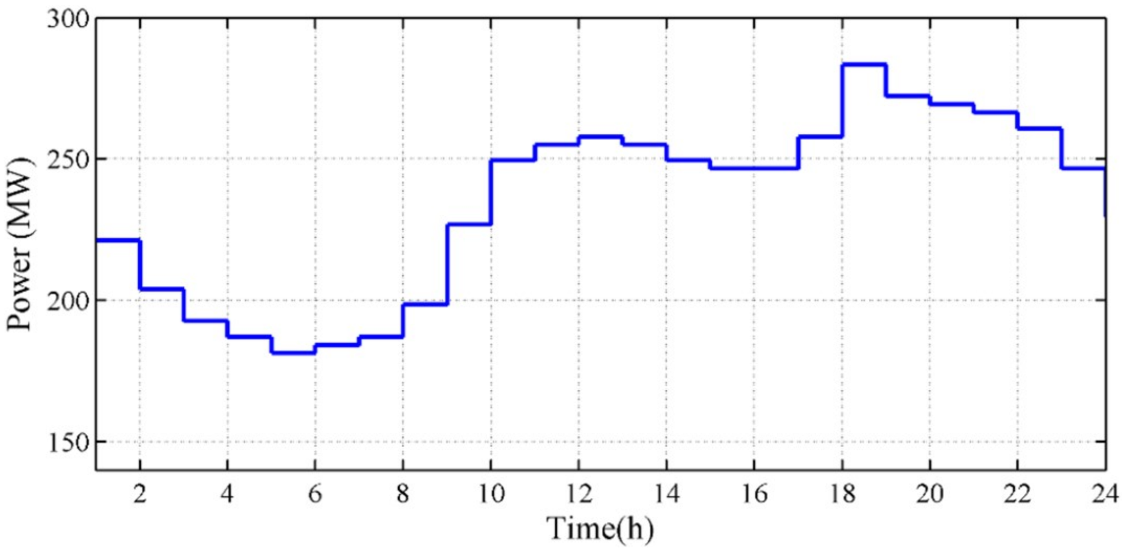

Figure 5. Hourly load profile [37]

Table 2. Data on EV fleets in the modified IEEE 30-bus system

EV Fleets	Number of EV	Home node	Work Node	Min. Cap. (MWh)	Max. Cap. (MWh)	Max. Power Exc. (MW)
O-F1	1500	1 (O1)	8 (O7)	32	180	26
O-F2	1000	1 (O1)	11 (O8)	22	120	16
O-F3	1000	5 (O2)	21 (O7)	22	120	16
O-F4	1000	7 (O5)	30 (O6)	22	120	16
G-F1	1500	14 (G4)	17 (G6)	32	180	26
G-F2	1000	18 (G3)	20 (G8)	22	120	16
G-F3	1000	15 (G2)	23 (G7)	22	120	16
G-F4	1000	13 (G1)	23 (G7)	22	120	16

Table 3. Mapping of EV transportation network data on the modified 30-bus system

Blue City	Node No.	Green City	Node No.
O1	1	G1	13
O2	5	G2	15
O3	9	G3	18
O4	28	G4	14
O5	7	G5	12
O6	30	G6	17
O7	21	G7	23
O8	11	G8	20

Table 4. Data on EV fleets in the modified IEEE 30-bus system

EV fleets	Number of EV	1^{st} Trip				2^{nd} Trip			
		Departure		Arrival		Departure		Arrival	
		Time	Bus	Time	Bus	Time	Bus	Time	Bus
1	1500	4.00	1	6.00	8	15.00	14	17.00	17
2	1000	5.00	1	6.00	11	14.00	18	15.00	20
3	1000	3.00	5	5.00	21	14.00	15	16.00	23
4	1000	3.00	7	4.00	30	15.00	13	16.00	23

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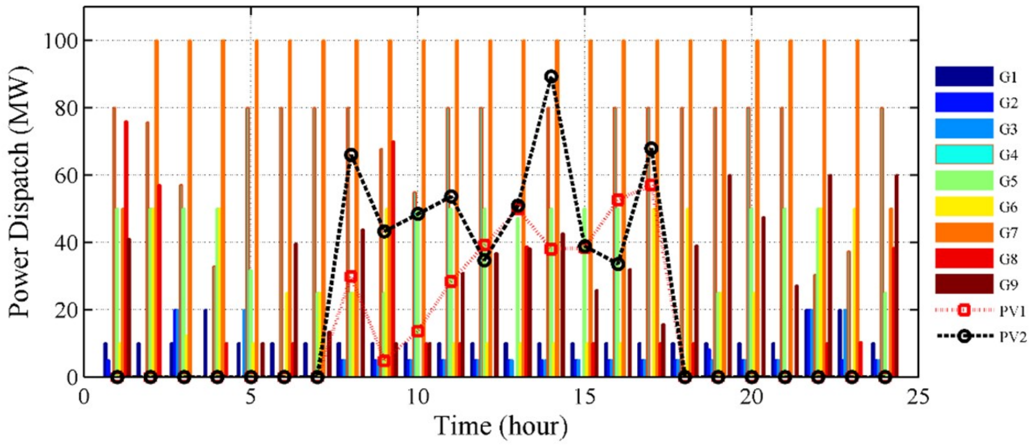

Figure 6. Dispatch of the generating unit with solar PV power

G4, and G6 are scheduled between 6 and 24 hours, although units G7 and G8 are scheduled between 21 and 24 hours. EV fleets may change the load profile of network energy, as illustrated in Figure 7. Between 16 and 17, when EV traffic is concentrated at Bus 4 and lines 1-4 are congested, demand peaks. Bus 1 is therefore unable to dispatch efficiently to satisfy the demand during this time. As a result, Bus 1 is incapable of dispatching effectively to meet the demand during this period. Moreover, the size of the network lines prevents G3 from scheduling efficiently. In this case, the total cost is \$198762.37, which is \$2560.39 lower than in Case 1, which used solar PV electricity.

Furthermore, the scheduling results for EV fleet charging and discharging in Case 2 are shown in Figure 7. Early in the day, when electricity prices are at their lowest, EV fleet units are charged, and between 6 AM and 2 PM, they are discharged. Buses 1, 5, 7, 11, and 30 are the main charging locations in Orange City, while buses 13, 15, 17, and 23 serve as the main discharging locations in Green City. This demonstrates that effective use of EV fleets and wind power can enhance the network performance.

The operator's required reserve in the day-ahead markets is shown in Figure 8. At hour 22, the up and down reserve is 38.78 MW and 18.78 MW, both of which are enough to cover altogether PV samples with thermal units. The outcome shows that the reserve market check is carried out in all cases. The reserve desired to be obtained in the day-ahead price as capacity at a discounted rate based on energy prices. The need for operating reserves is expanding because of increasing solar PV power penetration and anticipated load over the next years.

2.12 Case 3: Stochastic with EV fleets, solar PV, and DR program

This study integrates EV fleet, solar PV power scenarios, and transactive control using stochastic optimization in the scheduling framework. Uncertainty in solar PV power is handled using the QMCS methodology and the stochastic optimization technique. The Case 3 dispatch process using DR programs is shown in Figure 9. It is easy to determine that each EV fleet's DR program can eventually accomplish uniform load distribution by greatly lowering the original peak value and increasing its small valley.

For Case 3, the analysis includes the total daily energy savings of each EV fleet and the maximum incentive earned. Adopting DR programs resulted in a decrease in the generation of units G7 and G8, but an increase in the generation of the least expensive units G2, G4, and G6. Moreover, the costliest bus 30, which runs for 13–24 hours, is turned off for the duration of the scheduling 24 hours. The total running cost in this instance is \$196543.35. However, the uncertainty modeling of solar PV power has a significant impact on the final cost.

The load reduction and associated incentives that each EV fleet received are shown in Figure 10. The most willing EV fleets to lower their load have also accomplished the largest decrease and earned the best remuneration. Compared to other EV fleets that lowered load less, the EV fleets O-F2, O-F4, and G-F2, G-F4 that dropped the most load, earned larger incentives. The importance of the DR mechanism for EV fleets is demonstrated by this outcome. Like Case 2, EVs are discharged into the grid throughout the remaining hours of the study period after being charged early, during a period of low energy prices. Figure 10 displays the total charging/discharging power in five EV fleets. The acquired data show that the DR program and EV mobility can help the network if used properly. In this case, the EV fleet traffic is like O-F1 and G-F1 cities, considering one EV fleet. As illustrated in Figure 10, the EV fleet uses different charging/discharging techniques, notably after hour 12, to deal with the high-power load. Figure 11 compares the pricing of power in various scenarios while considering the thermal response, the availability of traffic power, the EV fleet, and the solar PV farm's consideration of the DR program. Case 1 for EV fleets, high power costs are attained during demand

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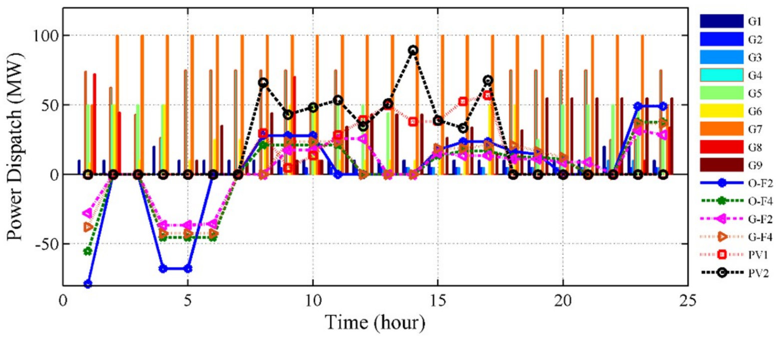

Figure 7. Dispatch of generating units with EV fleets and solar PV power

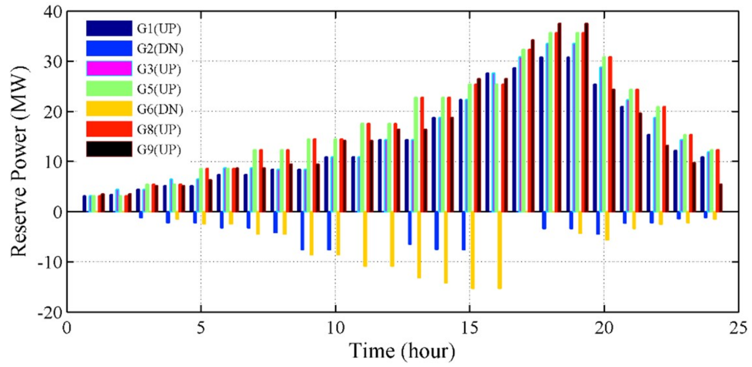

Figure 8. Reserve power with EV fleet and solar PV farm

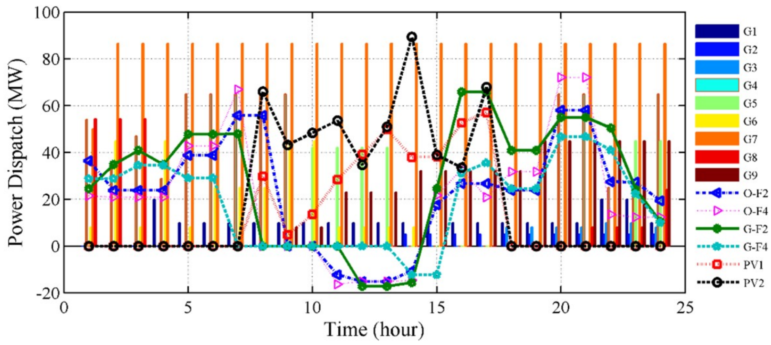

Figure 9. Dispatch of generating units with EV fleets and DR program

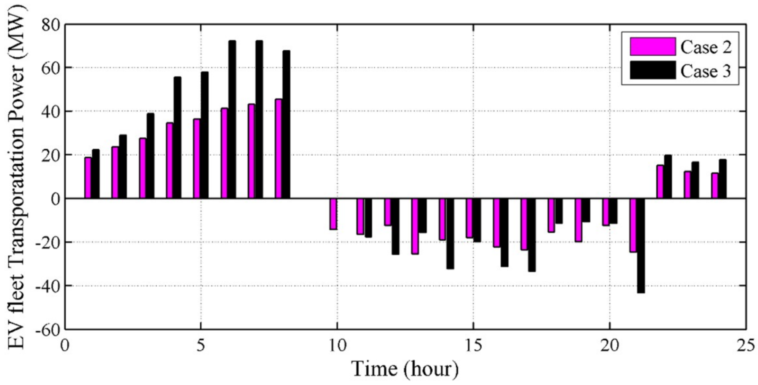

Figure 10. Charging/discharging power of EV Fleet for Case 2 and Case 3

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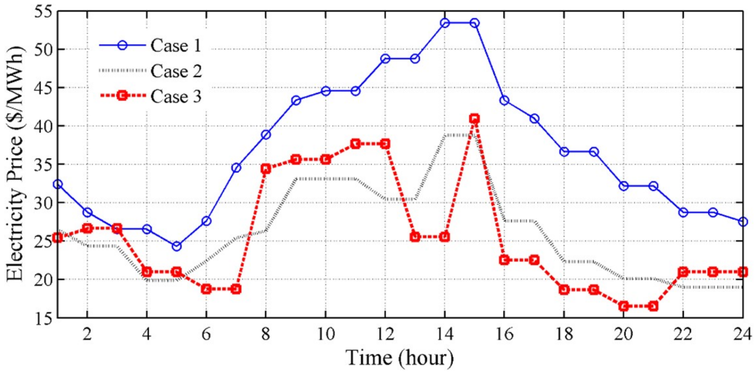

Figure 11. Price of electricity with thermal units in different cases

hours of 14 to 21 hours, and costs are high at peak load. Electricity costs during peak hours are reduced by EV fleets equipped with solar PV farms. Electricity prices are decreased during peak hours by the unit of EV fleets with solar PV farms and DR program, but prices are increased during off-peak hours, or between 8 and 12 hours. Figure 12 illustrates electricity and reserve pricing with a heavy load and demonstrates that reserve prices are highest when solar PV power is available at a low electricity price while taking thermal units into account.

2.13 Analysis of Transactive control

This section explores the advantages of transactive energy management by examining the EV fleet costs in Case 2 and Case 3. Table 5 shows the overall trade results, with Case 2's total EV fleet operational cost being $241.35 less than in Case 3. Energy exchange data indicate that each EV fleet relies significantly less on the grid when Case 3's transactive control is active. The detailed EV fleet operation costs for each fleet are presented in Table 6, supporting the claim that Case 3 reduces EV fleet operational costs at the structural level. The EV fleets at O-F3 and G-F3, which have negative expenses, are profitable in both scenarios despite not having an assigned EV to their on-site DR programs. Consequently, transactive control can be used to boost the utilization of DR program resources within the EV charging network stations.

2.14 Cost analysis

Table 7 illustrates the results of the dispatch cost for three cases. Since Case 1 ignores uncertainty, it has the lowest thermal cost. However, Case 2 examines the performance of EV users' systems throughout the intra-day economic dispatch stage, when they left their houses at 6 a.m. and returned at 5 p.m. In comparison to Case 3, the operational costs with EV fleets are higher at $198762.37 and $197532.54 for traffic assignment. The reason for this disparity is that the stochastic solution of Case 1 lacks robustness, making it unable to guarantee safe and dependable system operation in real-time. The improved performance of the energy market is consistent with these outcomes.

The total cost and simulation time for every case are described in Table 7. Three different sorts of EV consumers are also assumed in this scenario: 1) Early Party: leaves home at 6 a.m. and arrives back at 4.30 p.m. early; 2) Normal Party: leaves home at 7 a.m. and arrives back at 5 p.m. Early party EV fleets are O-F1, O-F2, G-F1, and G-F2, while standard party EV fleets are O-F3, O-F4, G-F3, and G-F4. In the first case, the total cost for the solar PV units is $201322.76. Without including EV fleets and the DR program, the base case thermal and reserve costs are $196543.35. When EVs are used, the total cost of the system is reduced by around $4779.41. Case 3 has the lowest traffic cost, whereas Case 2 has the highest, owing to improved network congestion caused by EV fleets and solar PV scenarios. The study evaluates how EVCS enhances system flexibility under different EV penetration levels. EV fleet size and solar PV capacity scale up proportionally, while thermal power plant parameters remain unchanged.

Figure 13 displays the net load variance at different levels of solar PV penetration. The net load is the difference between total energy use and solar energy generation. Without new sources, the system's current conventional production will inevitably be sufficient to meet the net load. The graphic shows five different solar PV penetration samples. Traditional units will experience less strain as solar PV penetration increases.

2.15 Sensitivity Analysis

The ability of solar electricity to meet the high demand rates of system operation is analyzed through a sensitivity analysis. The effect of different solar generation scenarios on the total cost is evaluated by increasing the load by 10% and 18%. As shown in Table 8, the percentage of cost reduction increases with a higher overall load. This analysis indicates that solar energy benefits the system when demand is high.

3. Conclusion

In this research, a transactive management condition conducted a thorough analysis of renewable power gen-

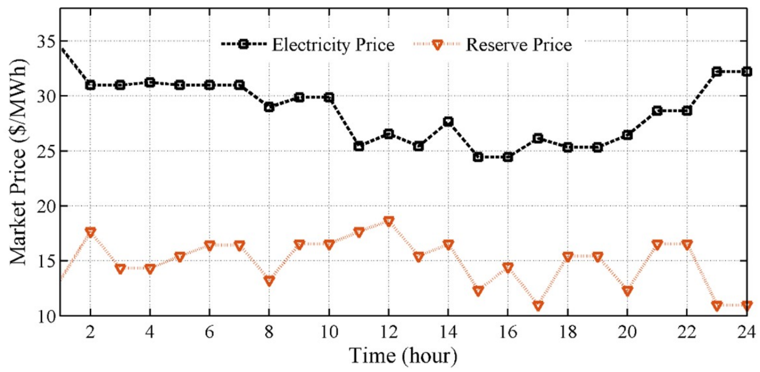

Figure 12. Price of reserve and electricity with thermal units.

Table 5. Transactive control IEEE 30-bus system for EV fleet traffic cost.

Cases	Traffic cost ($)	Energy trade in transactive control (MWh)
2	1076.11	–
3	988.42	1198.67

Table 6. EV fleet traffic cost operation in the IEEE 30-bus system

EV fleets	Case 2 ($)	Case 3 ($)
O-F1	76.77	54.55
O-F2	102.87	96.65
O-F3	-115.88	-101.66
O-F4	87.88	66.32
G-F1	107.67	88.77
G-F2	132.55	120.44
G-F3	-155.32	-163.87
G-F4	98.54	78.65

Table 7. Cost comparison of three cases

Cases	Overall operating costs ($)	Thermal costs ($)	Traffic costs ($)	DR costs ($)	CPU time (s)
1	201322.76	201322.76	–	–	456
2	198762.37	197532.54	1229.83	–	762
3	196543.35	195432.66	987.87	123.69	1021

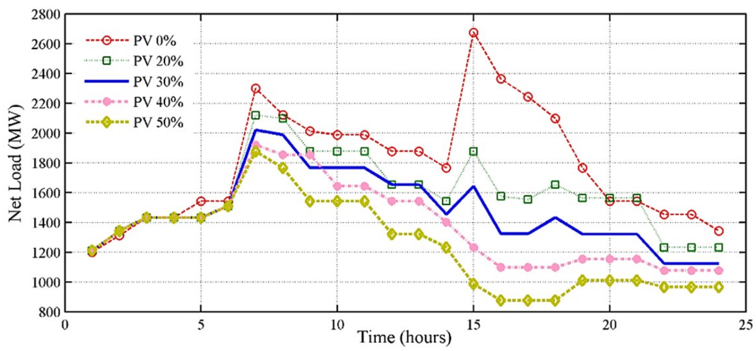

Figure 13. Net load for various solar PV penetrations

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Table 8. Cost comparison with varying solar PV penetration

Total system load	Minimized cost without Solar PV farm	Minimized cost with Solar PV farm	Decrease of optimized cost (%)
Forecasted load	$22314.76	$20986.66	6.32
Increased by 10 %	$23412.65	$21654.87	8.11
Increased by 18 %	$25432.22	$23232.76	9.46

eration and its impact on EV fleet and DR programs. This would ensure financial benefits for system operators, EV fleets and DR programs to participate in the transmission network. The constraints were reserve constraints, transmission constraints, EVCS constraints, thermal operation constraints, and DR program constraints. Compared to the traditional approach, the total cost shared by EV charging stations with uncertain solar PV and EV fleets is decreased by 1.288%, and the scheduling expenditures for EV fleets are decreased by 2.431%. However, by successfully minimizing load-shedding events and cutting operating expenses, the suggested approach exhibits improved economic performance in real intra-day operation. The system would be a MINLP problem, but these problems have local optima and take a lot of time. The analogous MILP model was developed in order to quickly achieve the global optimal solution with a small error. Uncertain parameters, like the quantity of EVs, and solar PV speed, were included in the model. As a result, the normal probability density function was used to characterize pertinent scenarios. The K-means scenario reduction technique was then used to extract the possibilities with high probabilities. When taking the DR program into account, the suggested methods may be cost-effective and efficient for power markets and load management. The findings demonstrate that the suggested method outperforms the stochastic method in terms of performance. The gap between the optimal solution of the proposed method and the lower bound of the theoretically optimal solution is very small. Overall, provides valuable insights into the optimization of solar PV-powered EV charging stations, enhancing their reliability and sustainability. Further research should focus on advancing loss allocation methodologies, leveraging AI-driven demand forecasting, integrating battery energy storage systems, and developing policy-driven incentives to optimize EV infrastructure deployment. Also, in future works, the hydrogen transportation systems will be integrated into the proposed model.

Authors contributions
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.
Availability of data
Data available within the article or its supplementary materials.
Template for data availability statement
All data generated or analyzed during this study are included in this published article [and its supplementary information files].
Conflict of interests
The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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