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An Evolutionary Game Theory-Based Optimal Scheduling Strategy for Multiagent Distribution Network Operation Considering Voltage Management

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ABSTRACT Distribution system operators (DSOs) have difficulty in scheduling distributed energy resources owing to the increasing power demand and penetration of renewable energy. The goal of this study is to determine the charging/discharging of PV energy-integrated energy storage system (PV-ESS), EV charging price, and demand response (DR) incentive values considering voltage management. To achieve the optimal energy operation for a distribution network, this study proposes an evolutionary game theory (EGT)-based new scheduling strategy, considering voltage management for a multi-agent system (MAS). The EGT, which is a decision-making strategy, is used by agents to cooperate and derive the best scheduling with their own behavior pattern functions to minimize the system operating cost. Photovoltaic-energy storage systems, electric vehicles charging power, and loads can perform charging/discharging scheduling, electric vehicle charging planning, and demand response participation, respectively. Under DSO supervision, a reward that stabilizes the voltage profile of the power distribution system is also implemented during the cooperation process. The proposed energy scheduling strategy combines an EGT-based decision-making with particle swarm optimization (PSO) to solve the optimization problem and determine the payoff function through self-evolutionary improvement. The effectiveness of the EGT-PSO has been analyzed for an IEEE 33-bus distribution system, and the results demonstrate that the proposed scheduling strategy not only achieves the most economical decision among agents but also manages the voltage profile.

INDEX TERMS Evolutionary game theory, distribution system operator, multi-agent system, optimal energy scheduling strategy, voltage management.

NOMENCLATURE

A. SETS

s / N^s	Set / maximum number of scenarios.
t / N^t	Set / maximum number of time periods.
$\#parking\ lot$ / $N^{\#parking\ lot}$	Set / maximum number of parking lots.
e / N^e	Set / maximum number of electric vehicles.
$b, i, j/N^b$	Set / maximum number of buses.
n	Set number of game theory iterations.
d	Set of particles dimension.
k	Set number of particles.
o/o_{max}	Set / maximum number of PSO iterations.
ij	Set number of branches.
s / N^s	Set / maximum number of scenarios.
t / N^t	Set / maximum number of time periods.
$*$	Optimal decision in Nash equilibrium.
$trial$	Set number of decision-making iterations.

B. PARAMETERS

P_l^{min}, P_l^{max}	Minimum and maximum active power flow of transmission line.

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V_b^{min}, V_b^{max}	Minimum and maximum of bus voltage.
P_{min}^{PV}, P_{max}^{PV}	Minimum and maximum power of PV.
P_{min}^{DR}, P_{max}^{DR}	Minimum and maximum amount of DR participation.
$P_{t,max}^{ch}$, $P_{t,max}^{dis}$	Maximum charging and discharging of ESS.
$SOC_{\min}$, $SOC_{\max}$	Minimum and maximum SOC of ESS.
$E_{nom}^{ch,e}$	Nominal charging power for e-th vehicle.
t_{a}, t_{b}	Arrival and departure time for e-th vehicle.
iw_o	Inertia weight for o-th iteration.
c_1, c_2	Learning rates.
r_1, r_2	Different random numbers from 0 to 1.
$pbest_o$	Best solution at o-th iteration.
$gbest_o$	Best global position at o-th iteration.
iw_{max}, iw_{min}	Initial and final inertia weights.
a_n, b_n, c_n	Decision of each agent.
$i_t^{ij,max}$	Maximum square of the current.
V_{min}	Minimum voltage limitation.
μ, σ	Mean and standard deviation.
η^{PV}, S^{PV}	Efficiency and area of PV generation.

C. VARIABLES

C^{Grid}	Cost function of transactional power.
C^{DR}	Cost function of DR.
P_t^{Grid}	Power from upstream grid.
Π_t	Market price of energy in time slot t.
P_t^{DR}	Participated capacity of DR.
μ_t^{DR}	Incentive value of DR.
P_t^{PV}	Power from PV.
P_t^{d}	Power demand.
P_t^{ESS}	Power from ESS.
P_t^{EV}	EV charging energy.
$P_{t,l}$	Active power flow of transmission line.
V_b	Voltage of each bus b.
$P_t^{ch,ESS}$	Power charged by ESS.
$P_t^{dis,ESS}$	Power discharged by ESS.
SOC_t	SOC of ESS in time slot t.
$E_t^{\#parkinglot,e}$	Power charged for e-th vehicle parked in parking lot # in time slot t.
Dem^e	Total power demand for e-th vehicle.
P_t^{ij}, Q_t^{ij}	Active and reactive power flow of brand ij.
I_t^{ij}	Current of brand ij.
R_{ij}, X_{ij}	Resistance and reactance of brand ij.
P_t^{j}, Q_t^{j}	Active and reactive load of bus j.
V_{avg}	Average of voltage profile.
$f_{\mathrm{B}}(SI)$	Behavior of solar irradiation.
λ_t	Times that random event occurs.
λ_{arr}, λ_{dep}	Rate of vehicles arriving and departing.

D. ABBREVIATIONS

ADN	Active distribution network.
EV	Electric vehicle.
ESS	Energy storage system.
DR	Demand response.
PV	Photovoltaic.
MAS	Multi-agent system.
PDF	Probability density function.
SOC	State of charge.
DSO	Distribution system operator.
EGT	Evolutionary game theory.
PSO	Particle swarm optimization.
EPSO	Evolutionary particle swarm optimization.
UPSO	Unified particle swarm optimization.
IPBDR	Intelligent price-based demand response.

I. INTRODUCTION

A. MOTIVATION

In recent years, the increase in energy consumption has affected the global economics and environment and caused reliability issues [1]. Great challenges have been put on both active power balance and voltage management for the active distribution network (ADN). Depending on the intermittence and uncertainty of weather conditions, renewable energy creates fluctuations in the voltage profile of the distribution network. Because electric vehicles (EVs) are also a new source of power consumption, the electrical load patterns become more unpredictable. These reasons make it difficult to manage and operate power systems. A distribution system operator (DSO) provides a promising solution for predefined energy issues through the renewable energy-integrated energy storage system (ESS), EV charging scheduling, and demand response (DR). The integrated photovoltaic (PV)-ESS unit that is installed in an active distribution network provides peak load shifting as well as reduces the purchased power from the upstream grid. Meanwhile, EV charging scheduling can decrease the passive influence of the charging load and reduce the operation cost. Moreover, the DR program is a beneficial resource as it reduces their energy consumption in response to financial incentives. Therefore, to alleviate energy crises, DSO should schedule distributed sources cooperatively to achieve the economic and reliable operation.

B. LITERATURE REVIEW

Multi-agent systems (MASs) contain numerous intelligent agents to distribute the burdens and produce efficient performance. Applications of MAS models are anticipated to be significant in the development of smart grids in various aspects of modern power systems, such as management, operation and control [2]. Since a MAS can operate the system flexibly, network management studies have investigated the overall management or scheduling, including generator scheduling, optimization, and economic power dispatching. An aggregation agent optimized the energy cost through coordination with the generation, load, and storage agents [3]. Meanwhile, the power system operation in MAS is concerned about the improvement of the reliability, flexibility, and continuous service for the distribution network. An incentive-based DR was implemented by determining the value of the incentive to minimize the operation and environmental costs, and operation risk [4]. Although the voltage of the distribution system should be controlled in real-time by adjusting the active and reactive power, handling them is difficult when new generators and loads are installed or during the intermittent operation of renewable energy resources.

The use of solar panels in distribution networks has significantly increased in recent years. PV power has gained increasing attention as a potential future main energy source, owing to its ability to generate electricity without any contamination. However, the power output is uncertain because the power generated by PV panels depends on the intensity of the solar irradiance. A probability density function (PDF) has been utilized to model the uncertainties of PV outputs and to express the behavior of solar irradiance [5]. As the distribution system focuses on the effect of power flow generated by distributed power sources, methodologies and approaches are needed to address the voltage rise. The integration of PV and ESS systems has been utilized as a solution in mitigating the impacts of PV uncertainty [6]. The authors in [7] discussed the integration of PV and ESS units for reducing energy loss and enhancing voltage stability. An optimal charging and discharging schedule of ESS was presented for voltage stability, peak load shaving, and reduction system operation cost. On the other hand, EVs charging will add additional power loads to the distribution systems, causing severe impacts if not managed properly. Previous studies presented different techniques to deal with coordinated EV charging [8]–[10]. A framework for optimizing EV charging in electricity spot prices was discussed from the perspective of an aggregator in [8], and an EV smart charging strategy based on electricity prices was proposed in [9]. However, both ignored the grid network loss and SOC of EVs. The authors in [10] proposed a coordinated strategy to control the charging load and minimize the electrical cost without considering EV charging on power system security. To minimize the power losses of distribution systems, a charging optimization method in [11] considered both the EV charging demand and voltage constraints using a two-layer optimization method. The authors determined the optimal locations and capacities of multiple PV units and the optimal charging of EVs for smart charging, namely V1G [12]. Although the method in [13] established an individual charging scheduling for each vehicle and avoided distribution grid congestion, there were insufficient strategies for considering the operation of other resources in the distribution system. Meanwhile, smart distribution networks have created an appropriate platform for the beneficial participation of DR in the optimal operation of power systems [14]. DR brings significant flexibility in the safe and optimal operation of power systems by providing an opportunity for active customers to reduce or shift some of their unnecessary consumption over peak hours in response to financial incentives or electricity price changes. The authors reported that the aggregators bid for the DR incentive and DR participators reduce the power capacity proportional to the incentive value [15]. The DR was applied to reduce the total operation cost and enhance the reliability of microgrid by adopting a bidding strategy using an aggregator [16]. A multi-objective-based optimal incentive-based DR scheduling was discussed, and the optimization methods were presented in [17]. However, the cooperative operation of renewable energy and DR in the system was not fully guaranteed in the optimization problem. Therefore, for economical and reliable operation, a strategy is needed to derive optimal scheduling while addressing the cooperation of the agents constituting the distribution network.

The economical operation can be defined as a multi-objective problem while satisfying the interests of each unit. The multi-objective models are divided into two groups, that is, optimality theory and game theory [18]. The optimality theory seeks the optimization combinations of the microgrid and the assets and environmental concerns. In contrast, the game theory aims to reach the social optimization with multiple utility companies and industrial electricity consumers. In addition, the game theory is considered a multiple decision-making process, whereas the optimality theory is a single-person decision-making process. All variables that affect the result are controlled by the decision makers in the decision-making process of the optimization theory. Meanwhile, in the decision-making process of game theory, the variables that influence the results are manipulated by many decision-makers, and the final results of decision does not solely depend on the decision-maker but also on the decisions of others [19]. A model for optimizing renewable energy in grid-connected microgrids interconnected with EV parking lots introduced a multi-objective framework that aimed to minimize the voltage fluctuations and excessive power losses [20]. In [22], the coordinated approach based on economic dispatch uses a DC power flow model for both transmission and distribution systems with the consideration of voltage constraints. A hybrid optimization algorithm was measured by a 25-bus microgrid in order to reduce the running costs of a virtual power player that collects renewable generation, EV, and DR. [23]. However, these types of energy resources have an effect on the voltage of the power system, so further consideration is needed. For these reasons, game theory is suitable for the scheduling approach proposed by this study, which is to determine the charging/discharging of PV-ESS, EV charging price, and DR incentive value considering voltage management. The authors in [23], [24] adopted the game theory strategy to solve the hourly DR incentive values and coordination strategy-based game theory that reduced EV charging cost. Furthermore, the existing game theory has a fixed payoff function that makes decisions for each agent, but the evolutionary game theory (EGT) improves the payoff function while repeating decision. In [25], [26], evolutionary optimization was proposed to address the energy resource management while maximizing income and minimizing the total cost of system resources with uncertain scenarios. However, since EGT is distinguished from the optimality theory, it satisfies the decision-making of individual energy sources and can find the optimal equilibrium. The application of EGT can derive the Nash equilibrium that maximizes or minimizes the objective function of all players [27]. In [28], EGT was used to express the behavior of consumers in the market. Moreover, EGT was used in the interaction between the operator and the end-user for efficient decision-making [29]. A study [30] on the interactions between different distributed energy sources, using fully-cooperative EGT, has shown that costs can be reduced by 15% compared to results without cooperation. The authors developed an EGT-based dispatch approach to deal with the constrained dispatch problem in microgrid, resulting in decreasing the electricity supplying costs by 2%. However, only few studies have been conducted on finding an optimal operation while satisfying the objective function of the distributed resources, such as renewable energy, EV charging station, and DR.

C. CONTRIBUTIONS AND PAPER ORGANIZATIONS

The aforementioned studies have studied their own methods to operating energy systems economically or reliably by scheduling the distributed power. However, an improved strategy using decision-making based on the behavioral patterns of each system is needed because the active distribution system becomes complicated due to intermittent renewable energy, EV, and DR participation. To this end, our work proposes an EGT-based scheduling strategy that realizes an economic and reliable operation. The DSO, which is a supervisor, determines PV-ESS charging/discharging, EV charging cost, and DR incentive value using EGT, thus improving the payoff function. The proposed strategy can derive the optimal scheduling of PV-ESS, EV, and DR considering the operating cost minimization and voltage management.

The major contributions of this study can be summarized as follows:

- The MAS model is constructed with a DSO agent, three PV-ESS agents, three EV agents, and a load agent in the modified IEEE 33-bus distribution network. It achieves a coordinated and efficient system operation using EGT based on the communication among agents to minimize the operating cost that consists of the electrical market price and DR incentive cost.
- The behavior pattern of each agent, which considers the uncertainties of PV, EV arrival/departure time, and EV required power, is adopted to optimize the objective functions of the agent. DSO can determine optimal ESS charging/discharging schedule, EV charging price, and DR incentive value while ensuring their degrees of freedom.
- The proposed EGT-based approach can present the optimal scheduling solution for minimizing the operation cost and managing the voltage profile in the distribution system. This assists the DSO in making a reasonable decision in terms of the economic consideration and reliability issues.
- An EGT-PSO algorithm is proposed, which can not only reform the payoff in the strategy but also improve the optimal solution and optimization accuracy through iterations. Comparison with other optimizers is presented to demonstrate the efficiency of solving the problem

The rest of this paper is organized as follows. Section 2 introduces the modeling of the active distribution system and multi-agent system. In Section 3, the problem formulation is described, and the evolutionary game theory is also introduced. Section 4 presents the proposed algorithm and overall solution procedure. Section 5 shows and analyzes the simulation results. Finally, Section 6 concludes this study.

II. SYSTEM MODELING AND OPERATION IN MULTI-AGENT SYSTEM

A. ACTIVE DISTRIBUTION NETWORK

In this section, we propose a charge/discharge scheduling strategy based on an ADN with integrated PV-ESS units and EV charging stations. It is necessary to identify the response of each system and develop a cooperative algorithm to produce optimal operations in DSO. The optimal operational scheduling should be able to reduce the operation costs due to the consideration of the voltage management by the DSO. Fig. 1 shows the grid-connected PV-ESS integration. Here, each non-dispatchable component must be converted to dispatchable renewable generation by the charging/discharging of storage systems. As a fast responder of ESS, inverter-based PV generation can control the intermittent renewable energy resource and deliver active power for simultaneous economic operation and voltage regulation. Therefore, the distribution network is permitted to schedule this system during a specific period in exchange for charging/discharging constraints.

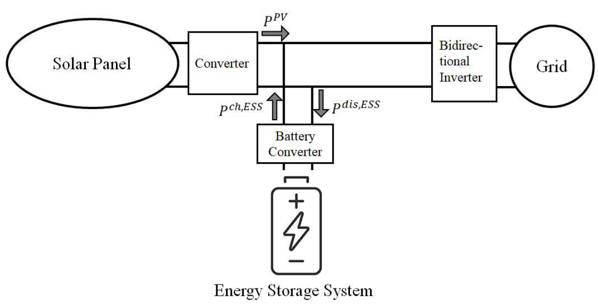

FIGURE 1. Integrated PV-ESS system.

EVs that charge at charging stations in parking lots have been managed by an aggregator due to their low energy capacities [31]. The parking manager can participate in scheduling to manage power demand and voltage by controlling the charging process by each EV. Moreover, smart charging management systems can decrease the passive influence of the charging load and minimize the operation cost of the charging managers because the charging behavior of each EV depends on the fluctuation of electrical market price.

The scheduling of EV charging, which aims to choose the appropriate time to charge, is set up based on its arrival time, departure time and the charging demand that is set by its owners. Fig. 2 depicts the schematic of the two-way communication structure between the active distribution system and multiple EV stations. EV agents managing the EV stations in parking lots have a relationship with the DSO in the charging price. In the system, there is a need for the DSO to coordinate EVs in order to meet the power requirement.

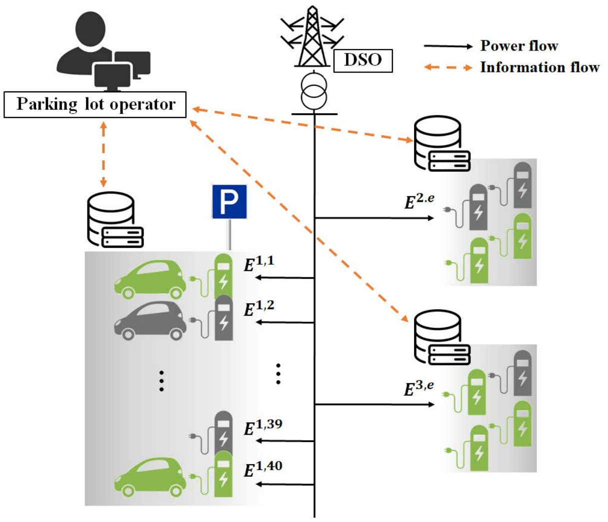

FIGURE 2. Schematic of aggregated EV charging stations with parking lots.

In addition, this program encourages loads to participate in DR since it is a flexible and inexpensive resource when power load reduction is required. DSO adjusts the incentive-based DR programs to decrease their electricity consumption based on a pay-as-bid strategy, which is applied to attract more DR participation during the peak period by offering high incentive values. In other words, it is assumed that high values increase the participation rate. Although incentive determination requires various factors, including the operating costs of the distribution system and voltage management, they can be considered in the system reliability. Therefore, active distribution system connecting the integrated PV-ESS units and EV charging stations can schedule charging/discharging power for units in a coordinated scheme to optimize the operation cost and voltage stability.

B. OPTIMAL OPERATION IN MULTI-AGENT SYSTEMS

The current ideas of solving distribution cooperative optimization problems can be broadly divided into two branches: centralized optimization algorithms and distributed optimization algorithms [32]. A centralized optimization scheme can be a good solution to coordinate power systems consisting of multiple generators and loads. However, this optimization scheme requires the collection and transmission of global information, which is costly, and it can suffer easily from single-point-failures. Hence, the whole centralized control system may need to be redesigned. Recently, MASs are regarded as one of the most popular distributed control solutions that have been applied for the operation and control of power systems [33]. A MAS is composed of several distributed intelligent agents that interact and cooperate within the environment, resulting in efficient task distribution that causes a faster decision-making process and operation. Since there are conditions that need to be considered to solve decentralized economic dispatch, each agents' objective function and constraints should be set [34]. In [35], the authors improved the convergence speed of techniques by computing the variables to each sub-problem. Therefore, it is essential to analyze the interactions between the agents, such as the recognition and determination of each agent behavior.

The detailed descriptions of each agent's role and decision-making process for the MAS model to work effectively are illustrated in Fig. 3. DSO acts as a supervisor to minimize the distribution and operation costs, including power transaction, EV charging, and DR incentive cost. Based on the wholesale electrical prices and economic dispatch in distributed system, the operator determines a set of electricity prices to EV charging stations and DR incentives to participants according to the economic dispatch in the distributed system. DSO considers the voltage variations over time of each bus and offers prices to achieve voltage stability for a day. Meanwhile, a PV-ESS agent schedules the ESS charging/discharging to produce a daily amount of dispatchable energy with predicted PV generation. Considering the voltage profile, DSO can also add to its strategy in the scheduling to minimize the renewable power loss. Moreover, the supervisor should consider both the EV charging load and DR participation, which change power demand patterns. The EV charging demand is scheduled to minimize charging costs. The charging demand is set based on the charging cost suggested by DSO. An EV agent collects the charging time (arrival and departure time) and the amount of power for each EV, and makes decisions on the charging price. Finally, the load agent aims to increase its profit by engaging in determining the incentive values, assuming that participation and incentive value have a positive correlation. When an operator suggests the value considering power load and voltage for each time period, the load agent presents the power reduction capacity accordingly. The Nash equilibrium is the point where the interest of each agent is negotiated. As a result, there is a need to discuss the decision-making strategies with this procedure because DSO coordinates with each agent to operate the distribution system to reduce the total operating costs.

III. GAME THEORY-BASED DECISION-MAKING STRATEGY

The role of DSOs for optimizing economic feasibility and stability becomes more important as power systems become increasingly complex due to distributed sources such as PV, ESS, EV and fluctuating loads. Game theory strategy is employed to capture the DR incentives associated with market prices. If the relationships are formulated considering the decision-making patterns of all agents, then complex

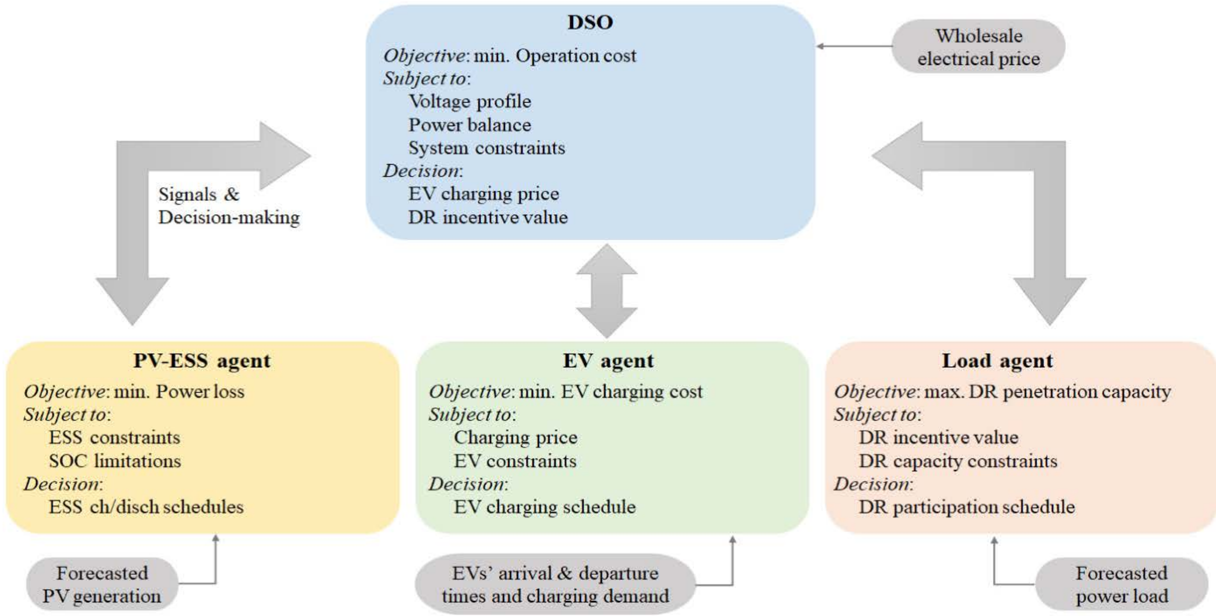

FIGURE 3. **Proposed scheme between the agents with the coordinated strategy.**

systems can be effectively operated. In this section, a problem formulation of the distribution system operation method is provided to minimize costs. Subsequently, the coordinated scheduling is considered using the evolutionary game theory, and the process of obtaining the schedules of each agent is presented with cost minimization and voltage stabilization.

A. SYSTEM FORMULATION

Since the behaviors between agents is involved in game theory strategy, the decision-making patterns should be derived based on the forecasted data. The objective function is to achieve the DSO's economical scheduling, charging/discharging schedule of the ESS, EV charging cost, and the DR amount, considering the stability of each bus voltage during the process.

1) OBJECTIVE FUNCTION

DSO aims to determine the operation of the distribution system, consisting of the electrical market price and DR incentives. The objective function that minimizes the operation cost is given by

$$F = C^{Grid} + C^{DR} \tag{1}$$

$$C^{Grid} = \sum_{t=1}^{T} \left[P_t^{Grid} \times \Pi_t \right] \tag{2}$$

$$C^{DR} = \sum_{t=1}^{T} \left[P_t^{DR} \times \mu_t^{DR} \right] \tag{3}$$

2) CONSTRAINTS

The equation for the power equality is one of the most important constraints and is the premise for the stable operation of grid energy management. The power generated by the resources must be equal to the power consumed by the loads.

$$P_t^{PV} + P_t^{Grid} = P_t^d + P_t^{ESS} + P_t^{EV} - P_t^{DR} \tag{4}$$

Equation (4) balances the generated power by PVs and the transacted power with the consumed power of consumers, the charged/discharged power by ESS, the EV charging energy, and curtailed power due to DR program. PESS is on the right-hand side of the equation because the ESS discharge is negative, and the charge is positive.

$$P_l^{\min} \le P_{t,l} \le P_l^{\max} \tag{5}$$

$$V_b^{\min} \le V_b \le V_b^{\max} \tag{6}$$

$$P_{\min}^{PV} \le P^{PV} \le P_{\max}^{PV} \tag{7}$$

$$P_{\min}^{DR} \le P^{DR} \le P_{\max}^{DR} \tag{8}$$

$$0 \le P_t^{ch,ESS} \le P_{t,\max}^{ch} \tag{9}$$

$$0 \le P_t^{dis,ESS} \le P_{t,\max}^{dis} \tag{10}$$

$$SOC_{\min} \le SOC_t \le SOC_{\max} \tag{11}$$

Equation (5) implies that the active power flow of lines does not exceed the transmission capacity limits. Moreover, the voltage of each bus b in (6), which is considered as a constraint, should be kept between the lower and upper amounts of the bus voltages. In addition, (7) and (8), which represent constraints, state the prohibited operation zones of PV and DR at time t, respectively. $P_{t,\max}^{ch}$ and $P_{t,max}^{dis}$, which are expressed in (9) and (10), are the maximum charge and discharge power. Finally, the constraint given by (11) is the upper and lower limits of SOC.

EVs act as power consumers while they are charging, and they leave the charging system after sufficient charge is stored to meet the power requirement for transporting individuals. In [36], a real-time EV charging scheduling strategy based on the optimization of 40 EVs charging in a parking lot improved the utilization rate of the PV power and reduced the electricity cost of the operators. Charging infrastructure provided a nominal charging energy of 7.7 kW in parking lots or EV fleets to derive the optimal scheduling [37], [38]. The mathematical equations of the EVs are as follows:

$$P_t^{EV} = \sum_{\#parking\ lot=1}^{3} \sum_{e=1}^{40} E_t^{\#parking\ lot,e} \tag{12}$$

$$E_t^{\#parking\ lot,e} = \begin{cases} E_{nom}^{ch,e} & k_t^e \geq 1 \\ E_{nom}^{ch,e} \cdot k_t^e & 1 > k_t^e > 0, \qquad t \in [t_a, t_b] \\ 0 & otherwise \end{cases} \tag{13}$$

$$\text{subject to } k_t^e = \frac{Dem^e - \sum_{t=1}^{t-1} E_t^{\#parking\ lot,e}}{E_{nom}^{ch,e}} \tag{14}$$

B. EVOLUTIONARY GAME THEORY

1) BACKGROUND OF EVOLUTIONARY GAME THEORY

For optimal scheduling of distributed resources within the system network, a multi decision-making process such as game theory is recommended instead of a single person decision process such as optimality theory for optimal scheduling of distributed resources within the system network. The game theory is adopted to achieve the optimal scheduling described above, consisting of PV-ESS charging/discharging, EV charging, and DR participation. Generally, there are the two groups of the game theory, such as cooperative or non-cooperative games. In cooperative game, communication between participants is often allowed; however, this is not permitted in the non-cooperative game. Situations in which communication is not allowed do not produce Nash equilibrium, which is defined as a stable decision based on the payoffs received by participants after their best choices. The one-shot character of non-cooperative games can miss the best choice as the Nash equilibrium is not similar to the Pareto optimal solution [38]. On the other hand, the game is repeated to improve the Pareto efficiency of the Nash equilibrium. In the process of finding satisfaction, each agent must establish their own objective function to understand and adapt to the changes of each other's strategies, assuming that the players in the game are rational. As the best result may not be achieved when playing the first game, the strategy to achieve the best equilibrium point by repeating the game while exchanging information with each other is needed, which is called the evolutionary game theory. However, it is not only a repetitive game, and an evolutionary stable strategy must be derived. In this paper, DSO aims to minimize the total operating cost by improving the scheduling through EGT.

Let $(x_{\text{n}}^*, x_{-\text{n}}^*)$ denote the Nash equilibrium of each agent i, and the payoff function is as follows.

$$\begin{aligned} P_n\left(x_n^*, x_{-n}^*\right) &\geq P_n\left(x_n^*, x_{-n}\right) \\ P_n\left(x_n^*, x_{-n}^*\right) &\geq P_n\left(x_n, x_{-n}^*\right) \end{aligned} \tag{15}$$

Appendix A.1 describes the theorem to prove that a unique solution exists in the proposed payoff function.

2) EGT-PSO

PSO, which is a population-based stochastic optimization technique, is used to establish the payoff function. Inspired by the social behavior of bird crowding, simulations are repeated to improve candidate solutions, which results in generating optimal solutions. This can be considered as a distributed behavioral algorithm that can perform d-dimensional searches to find solutions to various optimization problems. In the PSO algorithm, the kth object of the population in the dimensional search space is evaluated based on the objective function at the current position. Each particle has a d-dimensional position vector $X_k = [x_{k1}, x_{k2}, \ldots, x_{kn}]^T$ and velocity vector $V_k = [v_{k1}, v_{k2}, \ldots, v_{kn}]^T$. The velocity and position of particle k can be expressed in the $(o+1)$-th iteration.

$$\begin{aligned} \overrightarrow{V_k}^{o+1} &= iw_{o+1} \cdot \overrightarrow{V_k}^{i} + c_1 \cdot r_1 \cdot \left(pbest_{ok} - \overrightarrow{X_k}^{o}\right) \\ &\quad + c_2 \cdot r_2 \cdot \left(gbest_o - \overrightarrow{X_k}^{o}\right) \end{aligned} \tag{16}$$

$$\overrightarrow{X_k}^{o+1} = \overrightarrow{X_k}^{o} + \overrightarrow{V_k}^{o+1} \tag{17}$$

$$\text{subject to } iw_{o+1} = iw_{\max} - \frac{iw_{\max} - iw_{\min}}{i_{\max}}(o+1) \tag{18}$$

PSO offers the benefit of a fast convergence rate in power systems because there are no evolutionary algorithms [40], [41]. Note that fast convergence rate and accuracy are ideal for real-time optimization processes. However, PSO will likely be trapped in the local optimal state while processing some model features. Meanwhile, EGT is a reinforcement learning that rewards the right direction considering the dynamic behavior of each unit. When a game participant has a slow learning speed and low rationality degree, the replicator dynamic simulation mechanism will be suitable for the strategy adjustment in repetitive games with random pairing of large groups [33]. Therefore, EGT satisfies the internal interests of each agent, and DSO minimizes the system operating cost through PSO-based scheduling by coordinating their decision-making. The supervisor leads optimizations through self-evolutionary improvements because the opponent is not subjected to competition but rather to adaptation in the proposed algorithm. The evolutionary optimization of the proposed algorithm is different from that of the evolutionary PSO (EPSO) in [42]. To solve the coordinated security constrained, PSO algorithm is used based on transmission system operators and DSO [43]. This is because the PSO affects the payoff of EGT, inducing each agent to choose to cooperate, and the EGT does not directly affect the convergence rate of PSO. Therefore, this study presents a strategy to improve the decision-making scheduling using the EGT-PSO algorithm and also to reward the voltage management.

In the coordinated strategy, the opponent is not subjected to competition but rather to adaptation. The DSO is responsible for setting the orientation for the payoff function improvement. It makes the optimizations through self-evolutionary improvements by determining the convergence of the optimal result. Although the internal interest function of an agent is the same, this study aims to improve the input stimuli of DSO that induces scheduling.

Let (a_n^*, b_n^*, c_n^*) denote the Nash equilibrium of each agent, and the objective function is as follows:

$$f_n\left(a_n^*, b_n^*, c_n^*\right) \leq \begin{matrix} f_n\left(a_n^*, b_n, c_n\right) \\ f_n\left(a_n, b_n^*, c_n\right) \\ f_n\left(a_n, b_n, c_n^*\right) \end{matrix} \leq f_n\left(a_n, b_n, c_n\right) \quad (19)$$

The DSO derives the payoff function that reflects the operating costs and voltage variability after receiving information about scheduling from each agent. Therefore, a_n, b_n and c_n are the scheduling of PV-ESS, EV and DR, respectively.

In our study, the PSO-EGT among agents can be formulated as follows:

- Players: Agents participate in the game theory strategy.
- Strategies: Each agent decides its strategy by determining the usable power capacity and setting the costs to maximize its own purpose.
- Payoff: $f_{\mathrm{n}}(a_n, b_n, c_n)$ is a cost function for DSO.

In game theory-based strategy, each agent will take a scheduling strategy that maximizes/minimizes its own objective function based on the game theory-based strategy, as shown in Fig. 3. DSO derives the operating cost function by integrating them. At this point, the supervisor can adjust EV charging costs and DR incentive values to achieve load distribution and reduction in costs using the improvement of the payoff function in game theory. Moreover, our study presents the improvement of the voltage regulation in the distribution grid. In [37], [38], an advanced voltage regulation method was presented to maintain the voltages of customers within the permissible limits with an unbalanced load diversity, and the stabilize the output power of the energy resources in a distribution network. The power flow of a radial network was solved by the DistFlow branch model [44] and, a minimum voltage was 0.94 pu.

$$P_t^{ij} - \left(I_t^{ij}\right)^2 R_{ij} = \sum_{k \in \omega(j)} P_t^{jk} + P_t^j \quad (20)$$

$$Q_t^{ij} - \left(I_t^{ij}\right)^2 X_{ij} = \sum_{k \in \omega(j)} Q_t^{jk} + Q_t^j \quad (21)$$

$$\left(V_t^j\right)^2 = \left(V_t^i\right)^2 - 2\left(R_{ij}P_t^{ij} + X_{ij}Q_t^{ij}\right) + \left(I_t^{ij}\right)^2\left(R_{ij}^2 + X_{ij}^2\right) \quad (22)$$

$$\left(I_t^{ij}\right)^2 = \frac{\left(P_t^{ij}\right)^2 + \left(Q_t^{ij}\right)^2}{\left(V_t^i\right)^2} \quad (23)$$

$$0 \leq \left(I_t^{ij}\right)^2 \leq i_t^{ij,\max} \quad (24)$$

$$V_{avg} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{33} V_t^i \quad (25)$$

IV. OPTIMAL SOLUTION FRAMEWORK

PSO-EGT is applied with an improved payoff function to coordinate the decision-making of each agent and to solve the distribution network operation problem. With this solution framework, three game theory-based scheduling reached the Nash equilibrium, and DSO determines an optimal result that minimizes the daily operation cost. The distribution system operation with PSO-EGT is performed as follows:

Step 1: Design the distribution system model and initialize the input data (e.g., PV, EV, load, and electrical market price).
Step 2: Establish a stochastic model of uncertainties arising from renewable sources and EV
Step 3: Determine the capacity to participate in the DR program.
Step 4: Establish the objective functions and the corresponding constraints given by (1)–(14). Set the required input parameters to initialize the algorithm.
Step 5: Start the PSO-EGT algorithm loop for the n-th game theory.
Step 6: PSO is performed to set the payoff function between one agent and DSO while other agent decisions are fixed.
Step 7: Memorize the best scheduling for each agent that stabilize the average voltage given by (25).
Step 8: The scheduling is fixed and the game theory for others are carried out in the same manner. The decision-making proceeds in the order of EV, DR, and ESS with low degrees of freedom.
Step 9: DSO updates the value of scheduling parameters while considering the voltage stability to coordinate the scheduling of distributed units.
Step 10: Find and store the optimal solutions of the distribution system operation

V. CASE STUDY

A. DATA AND DESCRIPTION

The effectiveness and performance of the proposed EGT-based distribution system scheduling strategy have been examined on a modified IEEE 33-bus distribution network with a peak demand of 3715 kW and 2300 kVAr. Buses 12, 20, and 24 connect the integrated PV-ESS units, and sets of EV charging stations are located at buses 8, 25, and 30, as shown in Fig. 5. The validity of the proposed scheduling strategy is demonstrated on the east coast of USA [45]. The system load in half an hour for each bus is obtained proportionally based on the load curve presented in Fig. 6. It is assumed that the operational range of the bus voltages voltage is 0.94∼1.06 pu.

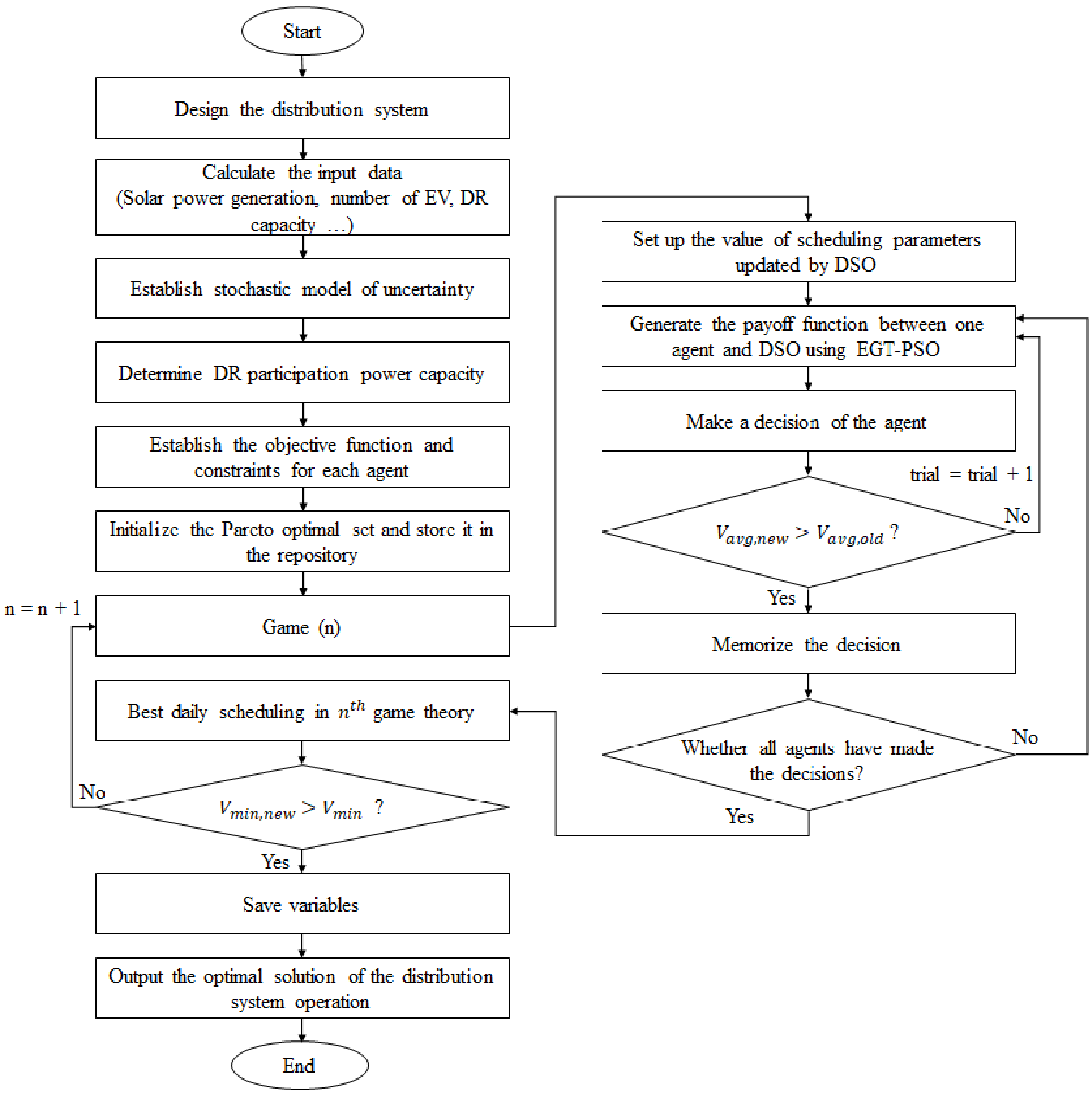

FIGURE 4. Overall decision structure of the proposed optimal operation scheduling.

The PV power generation output depends on weather conditions, especially solar irradiance. To describe the probabilistic nature of the solar irradiance, a beta PDF has been used for each time slot [12]. Appendix B describes the formulations of the beta PDF [46]. Table 1 lists the size of PV units and energy capacities of ESS units for each location in the distribution system. Considering voltage stability and operating cost reduction, the optimal charging and discharging schedules of the integrated PV-ESS system is developed for applications in the energy demand side to enhance the system electrical efficiency.

Due to lack of real-world EV charging data, the EV charging behaviors are modeled by following the Poisson distribution, which is generally adopted for traffic flow analysis [47]. Fig. 7 shows the arrival/departure time distribution and SOC distribution of drivers within a half hour. In this study, the arrival and departure times of EVs were set by giving higher arrival rate in the morning and higher departure rate in the afternoon. The lot manager is authorized to regulate the charging process for individual vehicles that are arriving in a specific time interval.

In order to validate the suitability of the proposed strategy, all cases were simulated with MATLAB R2020a installed on a personal computer with an Intel Core i5-8400 CPU @ 2.80 GHz processor and 16 GB RAM. For conducting the proposed EGT-PSO algorithm, the number of particles, the maximum number of iterations, and learning rates have been set as 3000, 100, and 2, respectively [24].

B. RESULTS AND ANALYSIS

The proposed scheduling for power system operation is based on the evolutionary game theory, where the DSO coordinates

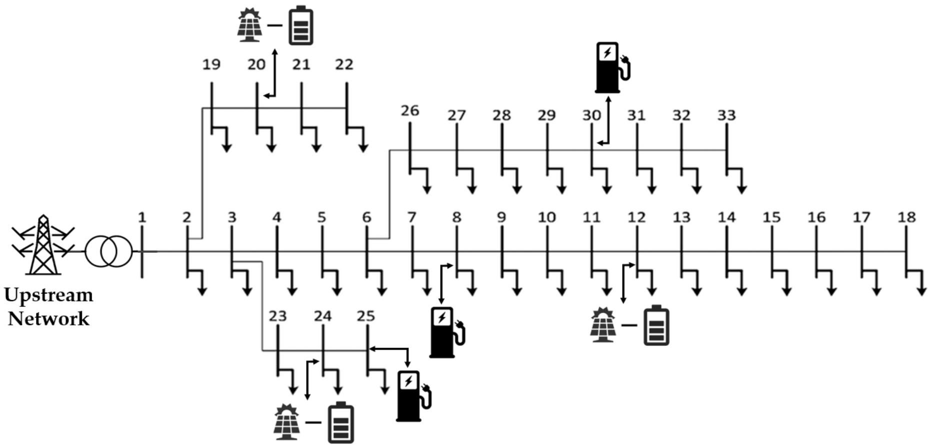

FIGURE 5. Modified IEEE 33-bus distribution system.

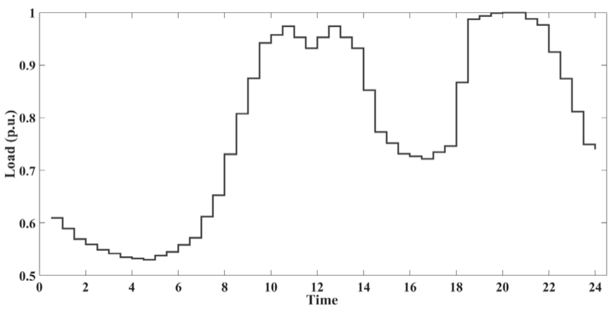

FIGURE 6. Normalized daily load data.

TABLE 1. Parameters of integrated PV-ESS units [6].

Bus	12	20	24
PV size (kW)	1858	526	1952
ESS power rating (kW)	773	220	810
ESS energy capacity (kWh)	5786	1.648	6115

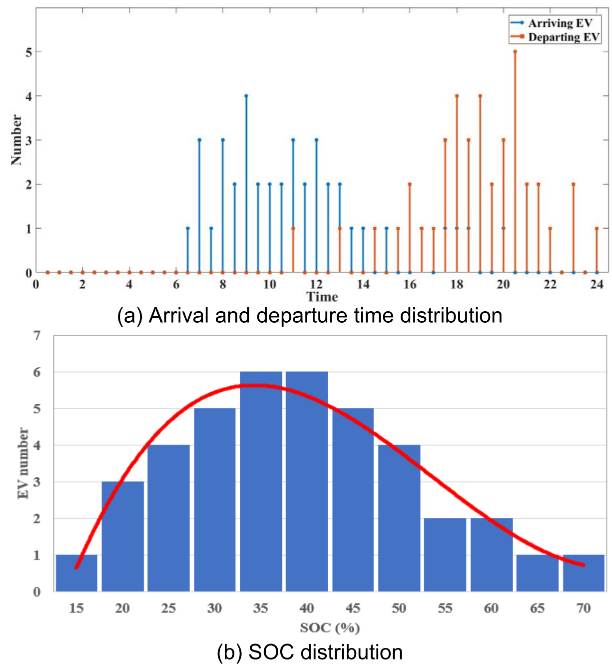

FIGURE 7. Forecasted data of EVs.

the scheduling of all distributed resources. The results of ESS scheduling, including charging/discharging power and SOC based on origin and posterity, are illustrated in Fig. 8. In the pre-coordination, the ESS repeats charging and discharging of a large amount of power to balance supply and demand without considering other adjustment factors, such as EV or DR. The maximum values of charging and discharging are 550 and 639.27 kW, respectively.

In addition, the minimum and maximum SOCs are 35.23% and 92.0%, respectively, as shown in Fig. 8 (a). After the adaption time organized by DSO, Fig. 8 (b) shows that the SOC of the ESS became flat, and its maximum and minimum values are 36.07% and 74.91%, respectively. ESS in bus 20 has a small capacity of 1648 kWh, as shown in Figs. 8 (c) and (d). In the first scheduling, the maximum charging and discharging power are 153.75 and 219.98 kW, respectively. In addition, the minimum and maximum SOCs are 21.87% and 61.59%, respectively. The posterity result shows a significant decrease in the number of times that ESS transitions from charging to discharging or vice versa. In addition, the SOC for one day is between 36.65% and 56.67%, as shown in Fig. 8 (d). In contrast, the battery in bus 24 is restricted during charging and discharging because it is linked to large-capacity photovoltaic power generation, as illustrated in Fig. 8 (e) and (f). From 9:30 a.m. to 3:30 p.m., ESS should charge renewable energy as much as possible

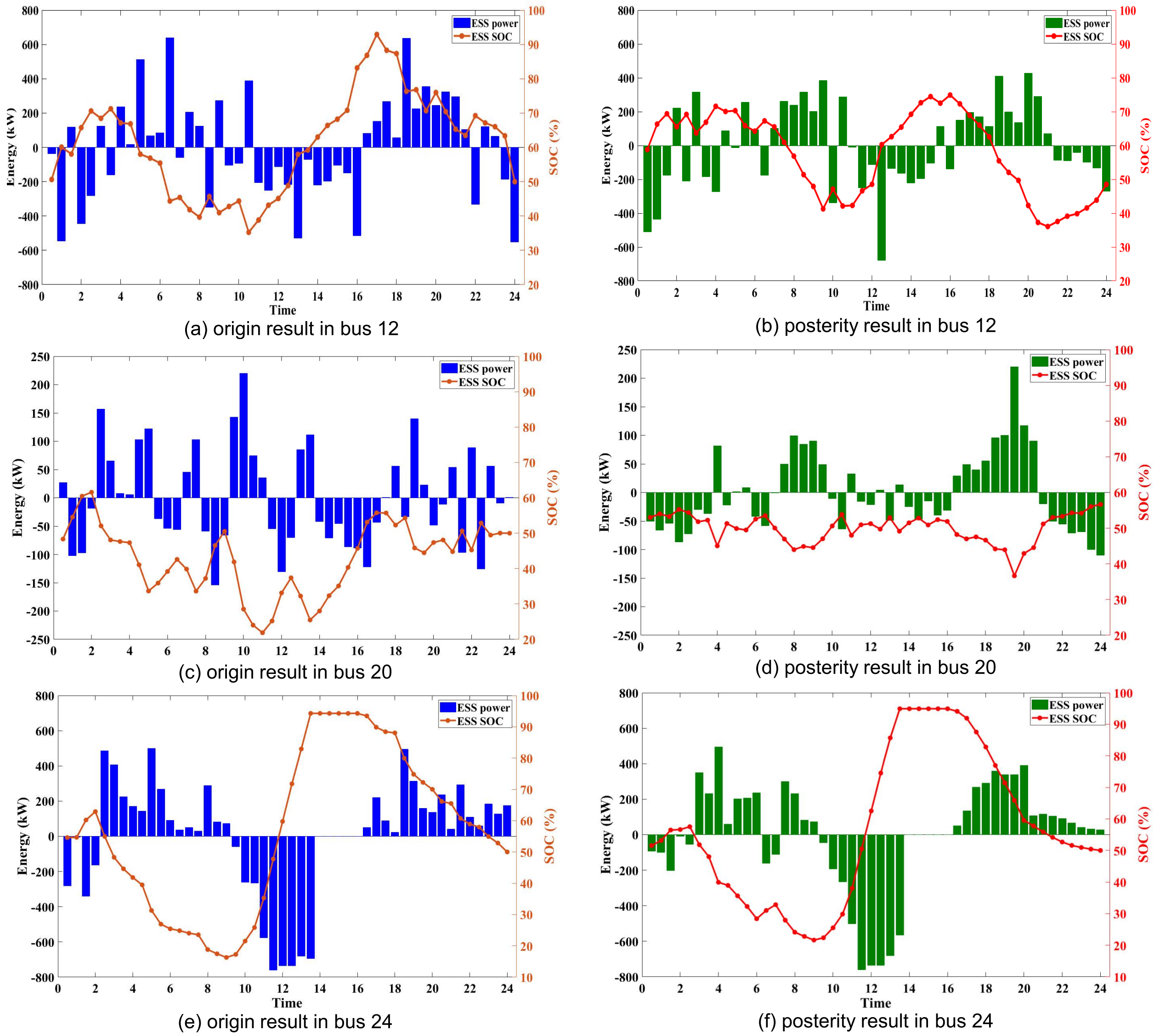

FIGURE 8. Optimal charging/discharging cycles and SOC of ESS.

because the amount of its power generated is higher than the total demand of buses 23 to 25. The maximum values of charging and discharging of the ESS are 760.52 and 499.87 kW, respectively, when there is no involvement of other factors. Similarly, the range of SOC change is approximately 16.29–94.28%, as shown in Fig. 8 (e). After DSO's cooperative strategy, ESS has the maximum charging and discharging power values of 760.52 and 495 kW. Figure 8(f) shows the slight improvement in the range of SOC, which is between 21.63% and 94.92%. This demonstrates that the proposed strategy facilitates the ESS charging/discharging scheduling, which improves the economic operation of the distribution system and reduces the range of SOC change.

To further study the impact of the proposed scheduling on the EV charging price, Table 2 compares the daily charging cost of the parking lots at the power market price using EGT-PSO. Depending on the SOC distribution, the charging costs at each parking lot based on the power market price vary. The value that EV agents must pay for charging decreases when using the proposed strategy. In parking lot 1, charging stations are connected to bus 8 and then the distribution of the power load takes precedence over decision making. At 1:30 p.m., the maximum charging power decreases from 242.9 to 163 kW. The main role of parking lot 2 is to utilize the large amount of renewable energy present in bus 24. This study decides to charge EVs by lowering the charging price regardless of the market price at the time of PV generation. Therefore, the charging cost reduction rate is the highest among the three parking lots. Similar to parking lot 1, parking 3 also aims to distribute the electricity demand. In particular, DSO set the charging costs at time slot considering the voltage drop since there are no renewable power

TABLE 2. Comparison of the EV charging costs among parking lots.

Parking lot	Number 1	Number 2	Number 3
Under power market price (US$)	180.37	172.47	183.82
Proposed strategy (US$)	171.72	107.77	165.85
Reduction rate (%)	4.79	37.52	9.78

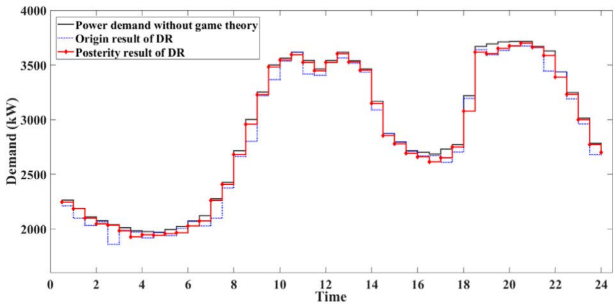

FIGURE 9. Results of daily load profile.

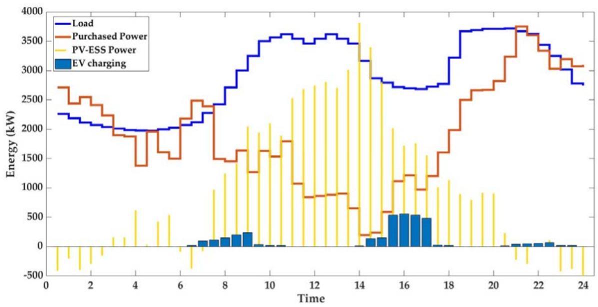

FIGURE 10. Optimal energy scheduling of modified distribution system.

plants nearby. It is apparent that the proposed strategy is an economic scheduling from the perspective of EVs and makes EVs the dispatchable resource that DSO can use for voltage stabilization and power distribution.

Fig. 9 shows the daily power load profiles of the distribution system based on the origin and posterity results. The DR strategy pursues the economic perspective and stability of the system by presenting reasonable incentives through decision-making between DSO and the load agent. In particular, the DR operating cost is 66.8 ¢/kWh when the first game theory is applied, which is more expensive than purchasing power from the upstream grid. In contrast, the evolutionary scheduling of DSO presents low incentives when renewable energy reduces the power demand and high incentives during peak time when the voltage drop occurs. After going through this adaptation process, the DR operation incentive is calculated as 12.5 ¢/kWh. As a result, the DR operating cost is reduced by 8.5% from 251.63 to 230.25 US$ using the DR game strategic scheduling.

Our study simulated the performance of the DSO using the EGT-PSO. The minimum voltage update is repeated 9 times, and the performance takes 153 s of CPU time. As shown

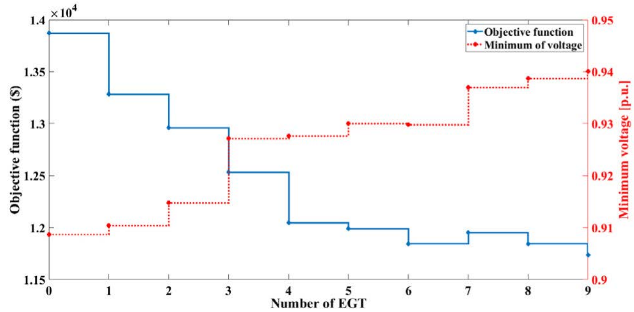

FIGURE 11. Objective function of the operation cost and minimum voltage management.

in Fig. 10, the amount of power purchased form the upstream grid was changed by the charging/discharging of PV-ESS and the additional power requirement of EVs. During the daytime when more solar power is generated, less power is purchased; further, electricity is purchased in a time zone when the wholesale price is low, thereby reducing operating cost. Fig. 11 shows the operation and minimum costs based on the number of EGT. Moreover, the operating cost decreases with the process of improving the payoff function since the agents are not subject to competition but rather to adaptation. Eventually, the proposed scheduling optimizes the objective function with a posterity result of 11735.9 US$, which is 15.4% lower than the cost of not applying the EGT-PSO. Moreover, the Nash equilibrium is derived from the 9th EGT because the algorithm ends when the minimum voltage of each bus is 0.94 or higher. The minimum voltage is improved from 0.9087 to 0.9401. Therefore, the EGT-PSO based scheduling strategy solves the coordinated optimization problem and improves the reliability of the distribution system through voltage management.

Performance comparison tests are implemented by comparing various PSO algorithms to demonstrate the suitability of EGT-PSO. Table 3 shows the optimal operation results of six algorithms. It is apparent that the EGT-PSO adopts reasonable costs of distributed resources and derives lower operating costs of 11735.86 US$ compared with the other algorithms. The PSO without the game theory cannot determine the EV charging price and incentive value. Subsequently, it optimizes the operation of the distribution system using only ESS charging and discharging. As a result, the total cost should have a higher value. In contrast, the unified PSO (UPSO) [48] and intelligent price-based demand response PSO (IPBDR-PSO) [49] focus on determining the EV charging cost and DR incentive cost, respectively. The total operation cost could not be exactly reduced because the distributed resources are not operated cooperatively. Meanwhile, the EV charging and DR costs are reduced by implementing the game theory which satisfies the objective functions of the agents. However, the application of EGT is more beneficial in terms of scheduling and costs than applying it only once. The operation cost of EGT-PSO is reduced by 15.42% and 11.66% compared to PSO and conventional game theory-PSO, respectively. Moreover, the EV charging cost and DR cost are reasonably

TABLE 3. Comparison of result.

Algorithm	EV charging cost (US$)	DR incentive (¢/kWh)	Min. voltage (pu)	Best solution (US$)	Worst solution (US$)	Average (US$)
PSO	536.66	66.8	0.9087	13538.31	14241.19	13874.82
EPSO	535.17	64.2	0.9079	13423.64	13890.05	13652.59
Game theory-PSO	517.42	25.6	0.9104	13071.72	13486.43	13284.65
UPSO	500.58	50.3	0.9217	12582.03	13275.60	12961.41
IPBDR-PSO	536.66	13.7	0.9286	12526.48	13092.87	12750.71
EGT-PSO	445.35	12.5	0.9401	11728.96	11810.07	11735.86

derived through the agents' cooperative decision-making. Accordingly, this study concludes that the proposed strategy is appropriate for minimizing the operating cost and satisfying the objective functions of agents based on evolutionary game theory.

VI. CONCLUSION

In this study, the EGT-based optimal scheduling strategy model was presented to operate the active distribution network economically and manage the voltage stably. The proposed approach coordinated PV-ESS units, EV charging, and DR program under the uncertainty variables in the ADN. Our study adopted the EGT strategy as an approach of decision-making in MAS, which has been effectively used for management, operation, and control of power systems while satisfying the objective functions of all agents. This derived a Nash equilibrium that assists DSO, such as supervisors, to suggest PV-ESS charging/discharging scheduling, EV charging cost, and DR incentive value. The main objective function of the optimization problem minimized the operating cost consisting of the purchased power cost and DR incentive cost. The cooperative problem was solved using EGT-PSO, which improve the payoff function to determine the convergence of the optimal result and satisfaction of the interests of each agent. The simulation results demonstrated a significant cost reduction of 15.42% under the proposed scheduling strategy as compared to conventional solutions. The proposed strategy provided DSO with the reasonable charging scheduling and incentive values and a solution to manage the voltage variability. As a result, the evolutionary scheduling reduced the purchased power cost, EV charging cost, and DR incentive cost. The comparison with other algorithms also confirmed the superiority of the proposed EGT-PSO in identifying the optimal solution. Therefore, DSO will be able to enhance the economic operation and the reliability of the power system by applying the proposed scheduling. This work can be further extended by considering various energy resources and by exploring their impacts on the reliability of the larger distribution network. Moving forward, the decision-making strategies of DSO agent in reserves, day-ahead scheduling, planning, and real-time markets could also be investigated for applying additional practical power market scenarios.

APPENDIX A

THEOREM OF THE GAME THEORY

Theorem to prove that a unique solution exists in the proposed payoff function is noted in [24], [50].

Proposition 1: For each agent i, the function P_n is continuously differentiable in x_n. Therefore, the space of agent payoff function is a non-empty convex compact subset of the Euclidean space in x_n.

Proof: The daily cost function $P_n(x_i, x_{-i})$ is continuously differentiable in x_n due to its continuous characteristics. Because the Hessian of $P_n(x_i, x_{-i})$ is a positive semi-definite, $P_n(x_i, x_{-i})$ is convex [51]. Proposition 1 is a prerequisite for Proposition 2.

Proposition 2: For $\forall i$, the Nash equilibrium of the cooperative game exists and is also unique.

Proof: Since the cost function P_n is convex in x_n, it has been demonstrated that the Nash equilibrium is present and also unique.

Proposition 3: The uniqueness of the Nash equilibrium, which is proven in Proposition 2, is the Pareto optimality.

Proof: According to Proposition 2, the evolutionary game has the Nash equilibrium among players. No one can change their payoff without permission. However, it is allowed to change the payoff based on the set value since the evolutionary game theory is in a cooperative relationship. Pareto optimality is defined as the opted strategy state when no one can increase their payoff by modifying the user's strategy without affecting the results of the other players. Consequently, it is noted that the Nash equilibrium in the game is the Pareto optimality.

APPENDIX B

UNCERTAINTY MODELING

- PV generation modeling

Beta PDF has been selected as an appropriate model to express the behavior of hourly SI [52]. The PV output power is expressed as

$$f_B\left(SI\right) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times SI^{(\alpha-1)} \times (1-SI)^{(\beta-1)} \quad \text{(B.1)}$$

where SI is ranging from 0 to 1. α and β are equal to or greater than 0, respectively.

The parameters α and β can be obtained using the following equations:

$$\beta = (1-\mu) \times \left(\frac{\mu(1+\mu)}{\sigma^2} - 1\right) \quad \text{(B.2)}$$

$$\alpha = \frac{\mu\beta}{(1-\mu)} \quad \text{(B.3)}$$

Given the SI for a specific time interval through the Beta PDF, the output power of PV can be defined as

$$P^{PV} = \eta^{PV} \times S^{PV} \times SI \quad \text{(B.4)}$$

- EV modeling

The arrival and departure time of the EV can be described as a discrete stochastic process by Poisson distribution.

$$P\left\{N_t = e\right\} = e^{-\lambda t}\frac{(\lambda t)^e}{e!} \quad \text{(B.5)}$$

Therefore, the number of vehicles arriving and departing respectively with rates λ_{arr} and λ_{dep} can be obtained as follows:

$$N_{EV,arr} = Poisson\left(\lambda_{arr}, t\right) \quad \text{(B.6)}$$

$$N_{EV,dep} = Poisson\left(\lambda_{dep}, t\right) \quad \text{(B.7)}$$

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