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Research Paper

An Optimal Interaction Model of Reconfigurable Smart Distribution System and Parking Lot Operators

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Abstract— *By leveraging the capabilities of Internet of Things (IoT) technology in conjunction with the smart grid concept and cloud-based data sharing, distribution system operators (DSOs) and parking lot operators (PLOs) can coordinate collaboratively to optimize techno-economic interactions. The integration of smart devices for data acquisition, monitoring, and control, along with cloud-based platforms for data storage, analysis, and collaboration, facilitates more efficient energy management, cost-effectiveness, and overall performance improvements. Building on these technological advancements, this study examines the daily operational planning of a smart distribution system in collaboration with PLOs, utilizing the Equilibrium Optimizer (EO) algorithm. Considering the potential of parking lots, the DSO aims to optimize both economic objectives and load leveling goals simultaneously, benefiting from structural reconfiguration for additional technical and financial gains. The model effectively incorporates constraints related to the expected and reliable operation of parking lots, as well as the security and radiality of the distribution system. By analyzing various objective functions and perspectives, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is used to determine the optimal state across all scenarios, achieving 60.3$, 5306.6 kW, and 716.8 kW for the first, second, and third objective functions, respectively. Numerical studies and simulation validations are conducted to evaluate the proposed model's performance, with results discussed in detail.*

Keywords—Smart distribution system, parking lot, optimal interactions, equilibrium optimizer, technique for order of preference by similarity to ideal solution.

1. Introduction

1.1. Motivation

The soaring energy demand in distribution systems has led to the proliferation of renewable energy resources and energy storage systems (ESSs) as indispensable parts of modern networks [1]. On the other hand, with the modernization and digitalization of transmission and distribution systems toward the smart grid concept, new distributed energy resources (DERs), such as electric vehicles, have emerged as significant players in distribution systems and urban areas [2]. These vehicles are charged in private homes or public lots operated by parking lot operators (PLOs). Although contributing to clean and carbon-free transportation, their uncontrolled and aggregated charging load can instigate serious challenges, such as feeder congestion, transformer overloading, and voltage drops in distribution networks. In this way, effective smart charging paradigms are essentially required [3]. On the plus side, data availability and cloud computing concepts have provided unique opportunities to optimize techno-economic interactions between distribution system operators (DSOs) and PLOs [4]. Energy storage and ancillary service provisions can be considered in these interactions [5]. These operators facilitate bidirectional interactions of energy and data between them. Specifically, upon receiving both technical and economic signals from the DSO, PLOs devise an optimal management strategy for the parking infrastructure, subsequently transferring this information back to the DSO [6]. Moreover, the inclusion of smart and remotely controllable devices, such as automatic switches, enables online, remote, and automatic topological variations within these systems. This process, which is referred to as the reconfiguration of distribution systems, stands out as one of the key strategic maneuvers with the potential to significantly impact energy management while concurrently enhancing technical and economic objectives [7, 8]. The ongoing study focuses on developing a smart reconfigurable distribution system encompassing techno-economic collaborations between PLOs and DSO. Specifically, the key objectives are to maximize parking lot benefits from the PLO's perspective to maintain their economic advantages and business model success. Then, the developed model aims to enhance the operational efficiency of the distribution system through structural reconfiguration and concurrent interactions with PLOs. In this process, load leveling and minimization of power losses are pursued by the DSO.

1.2. Literature review

Considerable research studies are conducted in the field of DSO and PLO optimal operation. The model developed in [9] proposes an innovative IoT-driven smart parking lot management approach that alleviates the limitations associated with communication range, energy consumption, and implementation costs. This system facilitates the detection of vehicles presence and transfers this information to a centralized server. The investigated system also

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hosts a solar-powered rechargeable energy storage system (ESS). The proposed model is anticipated to mitigate traffic congestion, optimize parking lot utilization, and enhance user awareness. Beside these benefits, the technical enhancements of distribution system, say as its capacity to minimize losses in the context of parking lot integration and load leveling, remain unaddressed. Furthermore, the potential contributions of distribution system reconfiguration towards achieving technical objectives have been overlooked. Manivannan in [10] has developed a machine learning approach for advanced energy management of hybrid electric vehicles equipped with energy storage capabilities. Within this framework, energy optimization techniques and algorithms are elaborated to mitigate operation costs and minimize charging durations. Furthermore, it strategically coordinates the charging of PEVs to avert new peak occurrence in load curves. However, some critical aspects such as PEVs aggregation and behavior in distribution system level has been overlooked. The interactive energy management of DSOs and PLOs, fostered for techno-economic benefits, are also overpassed. Topological modifications in reconfiguration process could also be further explored. Benefitting the topology variation, a stochastic two-stage framework for smart microgrid formation is developed in [11] which aims at maximizing restored loads; hence, enhancing its resilience. The analysis sheds light on the influence of various resources such as distributed and renewable generations, ESSs, and PEVs. A linear programming model, coupled with graph theory, is employed to determine the microgrid configuration facing with contingencies. Nevertheless, this investigation neglects collaborative operation PLOs and the microgrid operator. Also, it does not contribute to technical merits of reconfiguration. Through the introduction of an iterative optimization framework, the authors in [12] have developed a self-healing performance index to assess the resilience level of the multi-carrier energy system. This framework reduced the expected values of aggregated system and energy not supplied costs concerning. Note that this study has overlooked the possibility of collaborative energy interactions. Moreover, the distribution system model and topological reconfigurations are not considered. A similar attempt, considering the opportunities of reconfiguration and resilience enhancement, has been reported in [13] aiming at strengthening the grid resilience in the presence of DERs. An innovative network topology-based multi-objective optimization framework was proposed within which the economic and resilience metrics were enhanced while concurrently mitigating carbon emissions. Although the analytical findings, corroborated the efficiency of the developed model, the collaborative energy interactions and data sharing among the system participants and through the cloud mechanisms are not considered. The authors in [14] have developed a day-ahead scheduling framework deploying reconfiguration in microgrid scheduling, simultaneously within the distribution system. To mitigate the possible adverse impacts, the proposed framework integrates ESS and demand response programs at the network level, enhancing the operation adaptability and explores the power losses and voltage deviation minimization in network reconfiguration. However, the necessities of the parking lot's integration and their interaction in energy management have been evidently excluded. In the context of PEVs and DSOs cooperation, a recent model develops an advanced energy management system incorporating the capabilities of load and PEV aggregations and demand response programs [15]. The primary objective of the residential aggregator is to minimize the acquired power from the upstream network. Concurrently, the consumers aim to mitigate their electricity costs without compromising their comfort levels. This is while the objective of the community-level charging station is to minimize the aggregated costs associated with the charging and discharging of all PEVs. All of these expressions are formulated as an optimization process. Besides the recorded improvements in the investigated criteria, further improvements could be triggered by collaborations of PEV parking lots and network reconfiguration inclusion. High proliferation of PEVs in distribution systems and uncoordinated charging of these vehicles have been addressed in [16] demonstrating a possible feeder congestions and voltage security issues. An efficient model is proposed for optimal operation of PEVs charging and discharging by minimizing energy costs. Although some system-level issues are considered, the collaborations of PEVs parking lots and DSO and topological reconfigurations in both technical and economic indices improvements are not considered. Rao *et al.* in [17] have contributed an optimal model for locating PEV parking lots and maximizing the monetary benefits of PEV charging/ discharging. Some preliminary technical opportunities are also considered; however, the collaboration among the DSO and PLOs and the effect of network automation are not pursued in the established model. A transactive PEVs required energy management model is proposed in [18]. The initial objective has been the balancing of PEVs demanded energy within the supply capacity. However, the system level issues are not considered. For effective PEVs access and management, parking lots are optimally sited and sized in [19] within the first stage. Then, this study has explored the operational issues of the PEVs within these parking lots in the second stage. The need for coordinated and smart charging algorithms have been highlighted; however, the system-level opportunities and collaborations are not fostered. The added burden of PEVs on low voltage distribution networks voltage drops is investigated in [20]. Then, an optimal model is launched based on different resources available in the network level to maintain the voltage within the permissible range. However, the collaborative interaction of PLOs and DSO based on data sharing in cloud paradigm and the network reconfiguration impacts have not been investigated.

1.3. Contributions

Considering the reviewed literatures and the main focuses of the ongoing study as mentioned earlier in motivations, the following could be listed as the possible contributions and highlight of this study:

- **An optimal techno-economic cooperation model of PLOs and DSO:**
  Beyond the conceptualization, efficient mathematical modeling of PLOs and DSO interactions is launched and solved optimally, considering both the technical and economic objectives and constraints;
- **Ensuring business model success of PLOs:**
  By profit maximization, the business model success of PLOs is assured;
- **Concurrent minimum power losses and load deviations for DSO:**
  Following the profit maximization, the developed model incorporates the remaining capacity of PLOs in enhancing the operational indices of DSOs, say as assuring the possible minimum power losses and minimum voltage deviation;
- **Linearization and multi-attribute characterization of objectives:**
  Non-homogenous objective functions are treated in a linearized manner intended for computational goals and through multi-objective decision making approaches to determine the final compromise on solutions.

1.4. Manuscript structure

The remaining of this manuscript proceeds as follows. Section 2 presents the mathematical models of DSO and PLO operations, including their corresponding constraints, and addresses the optimization and solution method. With the aim of performance validation, Section 3 provides extensive numerical and simulation studies, along with further discussions and analysis. Finally, Section 4 gathers the concluding remarks.

2. Proposed Strategy

2.1. Fundamentals of the proposed model

The proposed model incorporates a smart distribution system that benefits from modern and intelligent devices, systems, and data sharing platforms. Fig. 1 shows the flowchart of the proposed model in three sequential stages. In the initial phase, the data concerning each bus within the distribution system is transmitted to remote terminal units (RTUs). Subsequently, the DSO undertakes a comprehensive analysis of the system's data, considering both technical and economic aspects. This evaluation is aimed at optimizing the planning and operation of the smart distribution system, as well as the efficient utilization of PEVs parking lots' facilities. In the subsequent phase, based on data sharing among the players, DSO devises some strategic plans for optimal placement of parking lots, determining the ideal number of PEVs for energy charging/discharging, and configuring the smart distribution system for optimal performance. This process yields the optimal system configuration and maximizes the utilization of parking lots. The DSO retains the flexibility to adjust the operation in alignment with their own and PLO's objectives and preferences. Additionally, the DSO undertakes the responsibility for safeguarding the distribution system against technical issues and ensuring its protection. To do so and mitigating the technical challenges, an energy management framework is developed to minimize day-ahead losses and load profile deviations of the distribution system. As the model provides the results for different objectives considering both the DSO's and PLOs' non-homogenous viewpoints, by employing the technique for order preference by similarity to ideal solution (TOPSIS) as a multi-attribute decision making approach, the optimal scenario is selected from a range of existing alternatives [21].

Note that although the established model and data sharing mechanism contributes to mutual collaborative benefits for both DSO and PLOs on technical and economic metrics, still several limitations persist. Some of these limitations could be listed for further explorations and research as follows, to mention but a few:

- **Data quality and availability:**
  The performance of these technologies hinges on the precision and accessibility of data. Suboptimal data quality may cause not-optimal energy distribution decisions;
- **System integration challenges:**
  Non-heterogeneous data sharing and integration systems based on diverse protocols could exacerbate the complexities associated with real-time data transfer, sharing, and decision-making processes;
- **Scalability concerns:**
  With an increase in the number of PEVs and the huge amount of data to be transferred and shared, the scalability issues might rise, limiting the practicability of these models;
- **Cybersecurity vulnerabilities:**
  In smart grid applications and paradigm performing based on data and automation concepts, the acquired data should be correct and reliable; hence, safe-guarding the data against bad-data injection and hackers would be of utmost priority;
- **Regulatory issues:**
  As some new systems, these systems and the corresponding data sharing mechanisms should be placed in some standard grid codes;
- **Initial capital costs:**
  Although the data presence and the subsequent systems running in this base represents unique opportunities, all of this requires remarkable investment costs.

2.2. Mathematical representation of the proposed model

The first priority is on maximizing the profits of parking lots participation from the perspective of the PLO. In Eq. (1), the income stemming from the energy interactions of the parking lot establishment with the distribution system is formulated.

$$Revenue = \sum_{Ls \in Ls_{disch}} \left[\begin{array}{l} Price_{Ls_{disch}} \times \left(\overbrace{P^{PEV} \times n^{PEV}_{Ls_{disch}}}^{P^{ParkingLot}_{disch}} \right) \times \\ \sum_{\bar{\lambda}} [SOC^{\bar{\lambda}}_{Ls_{disch}} \times (\%\bar{\lambda}_{Ls_{disch}})] \end{array} \right] \quad \forall Ls_{disch} \in Ls \tag{1}$$

Here, $Price_{Ls_{disch}}$ represents the energy price at discharge load states, P^{PEV} denotes the power of each PEV, and $n^{PEV}_{Ls_{disch}}$ signifies the number of PEV available for discharging task. Additionally, in this framework, $SOC^{\bar{\lambda}}_{Ls_{disch}}$ illustrates the state of charge (SOC) in different discharging states, while $\bar{\lambda}_{Ls_{disch}}$ indicates the percentage of each discharging state. Each state expresses the probability of each SOC. Within the proposed model, two cost components are considered for parking lots. The first component is associated with the PEV charging, while the subsequent one is linked to the yearly operational expenses of the parking lot. Both components are then formulated within the model.

$$Cost_1 = \sum_{Ls \in Ls_{Ch}} \left(\begin{array}{l} \left(\left(\frac{Price_{Ls_{Ch}}}{\mu_e} \right) + \mathrm{cost}_e \right) \times \left(\overbrace{P^{PEV} \times n^{PEV}_{Ls_{Ch}}}^{P^{ParkingLot}_{Ch}} \right) \times \\ \left[(1 - \sum_{\bar{\lambda}} (SOC^{\bar{\lambda}}_{Ls_{Ch}} \times \%\bar{\lambda}_{Ls_{Ch}})) \right] \end{array} \right) \quad \forall Ls_{Ch} \in Ls \tag{2}$$

$$Cost_2 = \sum_{Ls} \left[\left(\mathrm{cost}_{Ca} \times (n^{PEV}_{Ls_{Ch}} + n^{PEV}_{Ls_{disch}}) \right) \right] \quad \forall Ls \tag{3}$$

$$Cost = Cost_1 + Cost_2 \tag{4}$$

$Cost_1$ represents the cost of charging the existing PEV in the parking lot at their specific charge states. $Price_{Ls_{Ch}}$ denotes the charging cost and μ_e represents the impact coefficient of PEV charging equipment. $cost_e$ signifies the cost value of equipment damage due to additional usage for charging and discharging. $SOC^{\bar{\lambda}}_{Ls_{Ch}}$ represents the SOC for each charge state and $\%\bar{\lambda}_{Ls_{Ch}}$ indicates the probability percentage of each SOC. In the second cost component, $cost_{Ca}$ signifies the annual parking usage cost, while $n^{PEV}_{Ls_{Ch}}$ illustrates the number of PEVs available for charging at each charge state.

Considering the revenue and costs of parking lot, the objective function of maximizing benefit/profit form the PLO's point of view can be modeled as follows.

$$\begin{array}{l} OF_1 = Maximize \\ Benefit = \{Revenue - Cost\} \end{array} \tag{5}$$

To optimize the objective function OF_1, particular consideration must be given to relevant constraints concerning the quantity of PEVs engaged in charging/ discharging operations. It is necessary to keep the number of PEVs involved in charging activities during the specified study period equal to the total number of PEVs undergoing discharging processes within the identical temporal frame. This limitation, imposed by the parking capacity, is included in the model in Eq. (6).

$$\begin{cases} n^{PEV} = \sum\limits_{Ls \in Ls_{disch}} n^{PEV}_{Ls_{disch}} = \sum\limits_{Ls \in Ls_{Ch}} n^{PEV}_{Ls_{Ch}} \\ n^{PEV} - n^{Parking}_{Cpacity} \leqslant 0 \end{cases} \tag{6}$$

The second objective function considers the DSO's point of view and provokes the minimization of load curve deviation (LCD)

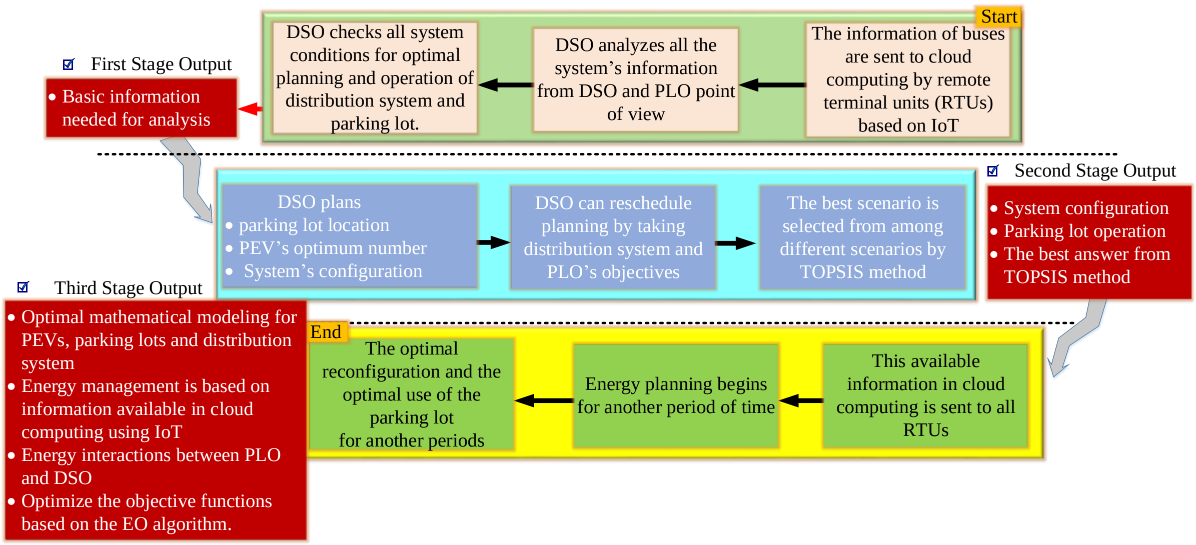

Fig. 1. Proposed strategy.

to have a uniform load profile. Hence, this objective function is formulated as follows.

$$OF_2 = minimize$$
$$LCD = \left\{ \sum_{Ls} \left| P_{Target} - P_{Load}(Ls) - P^{ParkingLot}(Ls) \right| \right\} \tag{7}$$

$$P_{Target} = \frac{\sum\limits_{Ls} P_{Load}(Ls)}{T = 24} \tag{8}$$

The goal is to make the load curve values closer to the mean value represented by the target value. Here, $P_{Load}(Ls)$ and $P^{ParkingLot}(Ls)$ denote the distribution system and the parking lot's loads, respectively. The parking lot load explicitly points to either PEVs charging or discharging powers, represented as follows for every state of charging or discharging processes.

$$P^{ParkingLot}(Ls) = \begin{cases} \sum\limits_{Ls \in Ls_{Ch}} \left(I^{PEV} \times P^{PEV} \times n^{PEV}_{Ls_{Ch}} \right) & \forall Ls_{Ch} \in Ls \left| P_{Load} < P^{Min}_{Target} \right. \\ -1 \times \sum\limits_{Ls \in Ls_{disch}} \left(I^{PEV} \times P^{PEV} \times n^{PEV}_{Ls_{disch}} \right) & \forall Ls_{disch} \in Ls \left| P_{Load} > P^{Max}_{Target} \right. \\ 0 & \forall Ls \,|\; P_{Load} < P_{Target} - \overbrace{\left(\frac{P^{Max}_{Target} - P^{Min}_{Target}}{2} \right)}^{P^{Margin}} \end{cases} \tag{9}$$

Based on Eq. (9), it can be inferred that if the distribution system load is less than the minimum target power (P^{Min}_{Target}), the parking lot would be in a charging state. If the distribution system loading level exceeds the maximum target power (P^{Max}_{Target}), the parking lot would be in a discharging state. If the distribution system load is in the margin region (P^{Margin}), the parking lot is neither charging nor discharging. In this context, I^{PEV} is a binary variable for the charging/discharging states of parking lot.

$$I^{PEV} = \begin{cases} 1 & \forall Ls \left| P_{Load} > P^{Max}_{Target} \right. \;\; \& \;\; P_{Load} < P^{Min}_{Target} \\ 0 & \forall Ls \,|\; P_{Load} \leqslant \;\; P_{Target} - \overbrace{\left(\frac{P^{Max}_{Target} - P^{Min}_{Target}}{2} \right)}^{P^{Margin}} \end{cases} \tag{10}$$

The third objective function, again from the perspective of the DSO, aims at minimizing the distribution system losses. Accordingly, Eq. (11) is considered.

$$OF_3 = \text{Minimize}$$
$$P_{Loss} = \sum_{Ls} \left\{ \sum_{k=1}^{N_K} (R_k \times I^2_{k,Ls}) \right\} \tag{11}$$

Here, R_k and $I_{k,Ls}$ represent the resistance value of and the current flowing through each branch in the distribution system. To enhance the solution possibilities of the proposed model, nonlinear terms are linearized. I^{PEV} and $n^{PEV}_{Ls_{disch}}$ are linearized as follows. Note that for the remaining components, a similar approach is considered.

$$-MAX^{disch}_{PEV} \times I^{PEV} P^{PEV}_{LS} MAX^{disch}_{PEV} \times I^{PEV} \quad \forall Ls_{disch} \in Ls \left| P_{Load} > P^{Max}_{Target} \right. \tag{12}$$

$$-MAX^{disch}_{PEV} \times I^{PEV} \leqslant P^{PEV}_{LS} \leqslant MAX^{disch}_{PEV} \times I^{PEV} \quad \forall Ls_{disch} \in Ls \left| P_{Load} > P^{Max}_{Target} \right. \tag{13}$$

$$-MAX^{disch}_{PEV} \times (1 - I^{PEV}) \leqslant (P^{PEV}_{LS} - n^{PEV}_{Ls_{disch}}) \quad \forall Ls_{disch} \in Ls \left| P_{Load} > P^{Max}_{Target} \right. \tag{14}$$

$$(P^{PEV}_{LS} - n^{PEV}_{Ls_{disch}}) \leqslant MAX^{disch}_{PEV} \times (1 - I^{PEV}) \quad \forall Ls_{disch} \in Ls \left| P_{Load} > P^{Max}_{Target} \right. \tag{15}$$

Here, the parameter MAX^{disch}_{PEV} assumes a substantial big value.

The constraints pertaining to voltage magnitudes at the distribution system nodes are declared as follows. It is essential for all buses to have the voltages within the permissible ranges. Similar limitations run for the current flowing from the branches, as well.

$$\begin{matrix} \begin{cases} V_{Min} - V^b_{Ls} \leqslant 0 \\ V^b_{Ls} - V_{Max} \leqslant 0 \end{cases} & \forall Ls, b \\ \left| V^1_{Ls} \right| = 1\, p.u & \forall Ls \end{matrix} \tag{16}$$

The total voltage deviation value considering all distribution system's nodes is computed by Eq. (17). This equation is formulated based on the per unit (p.u.) state, with the objective of minimizing the voltage profile deviation (VPD) from the nominal value of 1 p.u.

$$Voltage\,Profile\,Deviation\,(VPD) = \sum_{Ls}\left\{\sum_{b=1}^{33}\left|V_{Ls}^{b}-1\right|\right\} \tag{17}$$

In an AC load flow, the balance of active and reactive powers should be established in each bus of the distribution system, denoted by Eqs. (18) and (19). In these equations, the impact of reactive power of parking lot is neglected signifying that the exchanged power with the parking lot is predominantly active power.

$$P_{Grid}(Ls) - P^{ParkingLot}(Ls) - P_{Load}(Ls) = \sum_{m=1}^{N}\left(|V(n,Ls)|\,|V(m,Ls)|\,|Y_{n,m}|\cos(\delta(m,Ls)-\delta(n,Ls)+\theta_{n,m})\right)\ \ \forall Ls \tag{18}$$

$$Q_{Grid}(Ls) - Q_{Load}(Ls) = -\sum_{m=1}^{N}\left(|V(n,Ls)|\,|V(m,Ls)|\,|Y_{n,m}|\sin(\delta(m,Ls)-\delta(n,Ls)+\theta_{n,m})\right)\ \ \forall Ls \tag{19}$$

Here, $P_{Grid}(Ls)$ and $Q_{Grid}(Ls)$ represent input active and reactive power from the main grid to the distribution system. $V(n,Ls)$, $V(m,Ls)$, $\delta(m,Ls)$, and $\delta(n,Ls)$ respectively represent voltage values at buses n and m and angle values of bus voltages for load level Ls. $Y_{n,m}$ and $\theta_{n,m}$ denote bus admittance values and their angles.

Network radialilty constraint is considered in reconfiguration process and through RCSs inclusion. In this process, Eq. (20) denotes the relationship between the number of loops, number of branches, and the number of buses, assuring a radial structure.

$$N_{mL} = N_{br} - N_{bus} + 1 \quad \forall Ls \tag{20}$$

Various optimization algorithms could be employed to fine-tune the established model considering different objectives and constraints. The equilibrium optimizer (EO) algorithm, characterized by its dynamic mass balance principles, serves as a notable optimization engine. EO is in-depth explored and compared to conventional heuristic algorithms such as GA, PSO, and etc. where its outperformance is certified [22, 23]. It updates concentrations randomly based on viable equilibrium solutions, enhancing performance in early iterations while preventing local minima convergence later on. This balance helps adapt the parameters and reduces particle movement. In this way, EO consistently achieves optimal or near-optimal solutions more efficiently, with less computational time and fewer iterations across various applications. Accordingly, this optimization engine is contemplated to solve the established model.

3. Simulation Studies: Numerical Results and Performance Validations

3.1. Input data

As clarified earlier, in this study, EO is dedicated as the optimization engine implemented in MATLAB coding environment. In this algorithm, a constant that determines the exploration capacity is set at 1.83, while the constant that regulates the exploitation ability is set at 0.80. Moreover, the number of particles is fixed at 30 and the number of iterations is set to 500. These parameter values are based on a compromise between the characteristics of the objective functions and the specific outcomes. As depicted in Fig. 2, the IEEE 33-bus distribution system with its base topology is contemplated in numerical studies. The information about the lines and buses of the distribution system is given in [24]. Here, the DSO is the responsible for energy management processes.

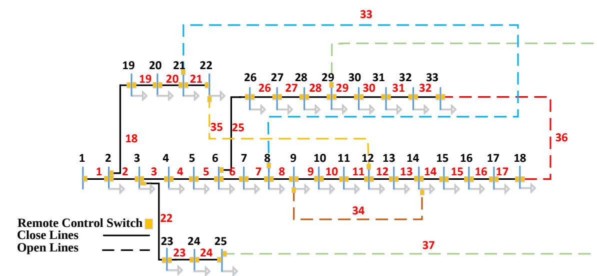

Fig. 2. IEEE-33 bus distribution system.

Table 1. SOC information of PEVs.

$SOC^{\lambda}_{Ls_{Ch}}$	$\%\lambda_{Ls_{Ch}}$	$SOC^{\lambda}_{Ls_{Ch}}$	$\%\lambda_{Ls_{disch}}$
0.0	40%	0.0	10%
0.2	20%	0.4	10%
0.3	20%	0.6	20%
0.5	10%	0.8	30%
1.0	10%	1.0	30%

The load curve of the system, considering hourly intervals, is shown in Fig. 3. From this figure, it is evident that the peak power of 3800 kW in the distribution system occurs at 3 p.m. The mean power consumption (P_Target), maximum mean power value (P_Target_Max), and minimum mean power value (P_Target_Min) are calculated at 2112.9 kW, 2218.5 kW, and 2007.2 kW, respectively. Furthermore, this investigation incorporates an evaluation of a parking lot accommodating 100 PEVs with an individual capacity of 10 kW.

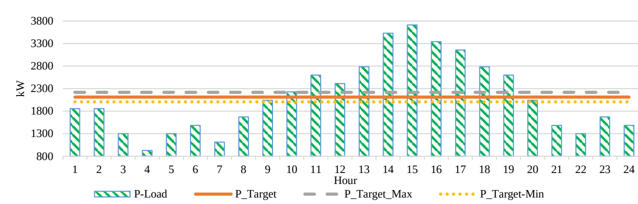

Fig. 3. Smart distribution system's load curve.

The PEVs charging intervals are designated between h1-h8 and h21-h24 according to the energy consumption patterns. Accordingly, the discharging periods could occur during h11-h19. Also, during time intervals h9, h10, and h20, the parking lot is in idol mode without any energy interactions with the DSO. The value of μ_e is assumed to be 0.9, while cost$_e$ and cost$_{Ca}$ are set at 0.125$/kWh and 0.432$/day, respectively. Additionally, the SOC related to charging and discharging of PEVs along with the percentage uncertainty of each SOC is provided in Table 1.

The electricity price signal is shown in Fig. 4. Seemingly, the electricity prices are lower during off-peak time intervals compared to peak loading hours. This difference in energy price instigates energy arbitrage opportunity for the end-use consumers.

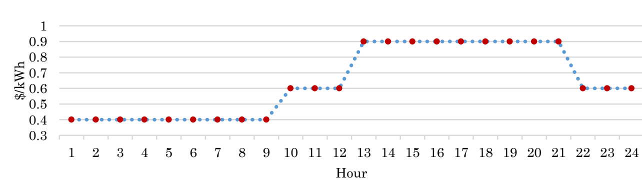

Fig. 4. The hourly electricity price.

3.2. Numerical results and performance validation

A) Initial results

Four distinct scenarios, each with three cases are considered in simulation studies, as follows:

- **Scenario 1:** The first scenario assumes the distribution system to be in its base configuration, without any system reconfiguration; additionally, the parking lot facilities are absent;
- **Scenario 2:** The second scenario considers the presence of parking lots in the distribution system within an interactive operation model; then, its impact on enhancing the objective functions, say as benefit maximization (OF_1), LCD minimization (OF_2), and power losses (OF_3) minimization are tailored without considering the influence of reconfiguration;
- **Scenario 3:** The third scenario explores only the optimal reconfiguration of the smart distribution system without considering parking lots. Similarly, its effect on the three objective functions is explored and compared to scenario 2;
- **Scenario 4:** This scenario considers the concurrent deployment of topological reconfiguration and parking lots presence in distribution system and assesses the investigated objective functions.

In addition to the outlined scenarios, this study considers three different cases, each corresponding to one of the three objective functions. Table 2 presents the results of each scenario across these three cases. The reported data of scenario 1 shows that when the parking lot facilities are absent, there is not any potential advantage and the system performance depreciates, sensibly. The second objective function within this scenario, pertaining to the deviation of the load curve from the margin area, is quantified at 16,067 kW; while, power losses, as the third objective function, are measured at 1,783.7 kW. Furthermore, the daily voltage deviations of all system's buses and across the scheduling hours is computed at 23.93 p.u. Notably, in this scenario, without system reconfiguration, lines 33, 34, 35, 36, and 37 are identified as radial components within the distribution system.

In case 1 of scenario 2, where the first objective function is only prioritized, the objective function is quantified at 424.70$. Subsequently, in cases 2 and 3, the second and third objective functions are emphasized, resulting in values of 5,586.4 kW and 1,699.5 kW, respectively. Furthermore, the presence of the parking lot results in reductions of around 10,480.6 kW and 84.2 kW in the values of the second and third objective functions, indicating a favorable influence on the distribution system operation.

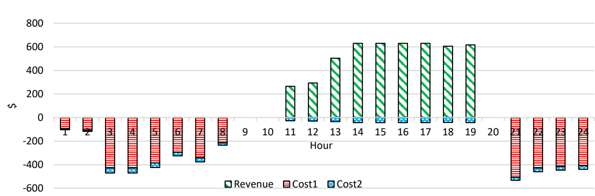

Fig. 5. Parking lot benefit in scenario 4-case 2.

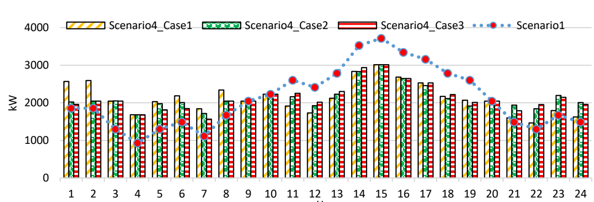

Fig. 6. The distribution system's load curve in scenario 4.

In scenario 3, due to the absence of the parking lot, the first case is omitted from the investigation. In cases 2 and 3, the second and third objective functions are respectively explored, resulting in values of 16067 kW and 696 kW for the objective functions, respectively. Comparing the obtained results with those of the scenario 1 highlights that system reconfiguration diminishes the third objective function by approximately 1087.7 kW, signifying a beneficial impact on reducing power losses within the distribution system. However, as the overall power consumption remains unchanged, there is not any remarkable effect on LCD improvement and the consumption curve remains unchanged, too. Additionally, as a same pattern of reconfiguration is for both cases in scenario 3, the power loss values obtained for these cases are equivalent. Following optimal reconfiguration in this scenario, lines 7, 9, 13, 31, and 37 are identified as open lines within the distribution system.

The objective function values obtained for each case of scenario 4 are 404.3$, 5306.6 kW, and 713.3 kW, respectively. Comparative analysis of this scenario with scenario 1 demonstrates that simultaneous presence of the parking lot and system reconfiguration option substantially enhances the first objective function by 404.3$, and the second and third objective functions by 10760.4 kW and 1070.4 kW, respectively. This highlights the positive impact of reconfiguration and parking lot integration on mitigating LCD and reducing losses within the distribution system. Moreover, enhancement in VPD in scenario 4 compared to scenarios 1 and 2 is substantial; albeit, not surpassing that of scenario 3. Exclusion of VPD in scenario 4 versus scenario 3 shows that the presence of a parking lot has negligible influence on VPD improvement; rather, it is the reconfiguration that holds the potential to improve VPD. Following the optimal reconfiguration in this context, lines 7, 11, 12, 31, and 37 are identified as open lines within the distribution system. Additionally, the optimal positioning of the parking lot for scenarios 2 and 4 is determined at buses 23 and 28, respectively.

B) TOPSIS-driven priority determination of solutions

As seen, there are many different cases and scenarios considering the different objective functions ahead of the decision makers and operators. To make a compromise and include all of the participants' priorities, TOPSIS approach is deployed. As shown in Table 3, there exist nine distinct states with specified values for each of the objective functions. The assignment of weights to each objective is dedicated based on its relative significance. In this investigation, to motivate the parking lot presence and foster the collaboration between PLOs and DSO in energy management for enhanced profitability, the weight attributed to the first objective function is set at 0.5. This is while, the second and third objective functions, which are from the DSO's perspective, are dedicated the weights of 0.25 and 0.25, similarly. Based on the results recorded in this table, the second state within the scenario 4 (scenario 4-case 2) emerges as the best result for all participants, say as PLOs and DSO. Within this prioritized hierarchy, the resulted benefit from the parking lot approximates 60.3$, with the quantified values for the second and third objective functions to be equal with 5306.6 kW and 716.8 kW, respectively. The cash flow of the parking lot in scenario 4-case 2 is depicted in Fig. 5. As demonstrated, the parking lot attains profits by discharging power during peak consumption periods while charging the PEVs during the light load conditions; thereby, culminating in an optimized charge/discharge strategy. The data presented in this figure indicates that during specific time periods, notably at 9, 10, and 20, as the PEVs are absent, there is not any record of improvement in both costs and profits. By scrutinizing the priority of the results, it is evident that the three first priorities belong to scenario 4, signifying it as the most efficient techno-economic scenario. For more details and performance analysis, a comparative analysis is hence conducted between the outcomes of scenarios 4 and 1.

C) Comparative results and discussions

As shown, scenario 4 reflects the best results among the investigated scenarios and cases; hence, justifying a comparative and in-depth study with the base scenario. The load profile of

Table 2. Simulation results.

Scenario	Case	Item	Value
Scenario 1		OF_1=Benefit ($)	-
		OF_2=LCD (kW)	16067 kW
		OF_3=Ploss (kW)	1783.7 kW
		VPD	23.93 p.u.
		Open Lines	33-34-35-36-37
Scenario 2	Case 1	OF_1=Benefit ($)	424.7$
		OF_2=LCD (kW)	7695 kW
		OF_3=Ploss (kW)	1757.8 kW
		VPD	23.96 p.u.
	Case 2	OF_1=Benefit ($)	121.2$
		OF_2=LCD (kW)	5586.4 kW
		OF_3=Ploss (kW)	1727.9 kW
		VPD	23.96 p.u.
	Case 3	OF_1=Benefit ($)	117$
		OF_2=LCD (kW)	7166.6 kW
		OF_3=Ploss (kW)	1699.5 kW
		VPD	23.95 p.u.
		Open lines	33-34-35-36-37
OF_1 Point of view (case 1) OF_2 Point of view (case 2) OF_3 Point of view (case 3)			
Scenario 3	Case 2	OF_1=Benefit ($)	-
		OF_2=LCD (kW)	16067 kW
		OF_3=Ploss (kW)	696 kW
		VPD	6.62 p.u.
	Case 3	OF_1=Benefit ($)	-
		OF_2=LCD (kW)	16067 kW
		OF_3=Ploss (kW)	696 kW
		VPD	6.62 p.u.
		Open lines	7-9-13-31-37
Scenario 4	Case 1	OF_1=Benefit ($)	404.3$
		OF_2=LCD (kW)	6730 kW
		OF_3=Ploss (kW)	725.4 kW
		VPD	7.471 p.u.
	Case 2	OF_1=Benefit ($)	60.3$
		OF_2=LCD (kW)	5306.6 kW
		OF_3=Ploss (kW)	716.8 kW
		VPD	7.468 p.u.
	Case 3	OF_1=Benefit ($)	87.9$
		OF_2=LCD (kW)	6143.1 kW
		OF_3=Ploss (kW)	713.3 kW
		VPD	7.466 p.u.
		Open lines	7-11-12-31-37

Table 3. Ranked priorities of the obtained results.

Scenarios	States	OF_1	OF_2	OF_3	Ranking
Scenario 1	State 1	-	16067 kW	1783.7 kW	9
Scenario 2	State 2	424.7$	7695 kW	1757.8 kW	6
	State 3	121.2$	5586.4 kW	1727.9 kW	4
	State 4	117$	7166.6 kW	1699.5 kW	5
Scenario 3	State 5	-	16067 kW	696 kW	7
	State 6	-	16067 kW	696 kW	8
Scenario 4	State 7	404.3$	6730 kW	725.4 kW	3
	State 8	60.3$	5306.6 kW	716.8 kW	1
	State 9	87.9$	6143.1 kW	713.3 kW	2

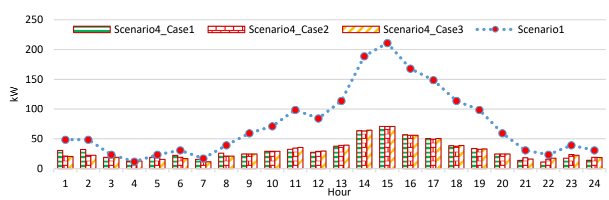

Fig. 7. The distribution system's power losses in scenario 4.

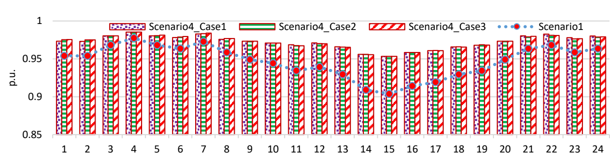

Fig. 8. Minimum bus voltage in scenario 4.

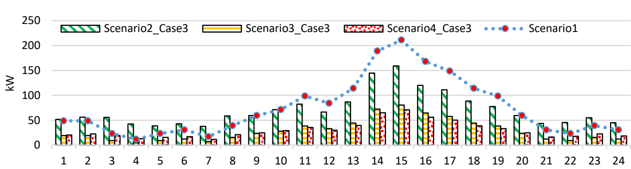

Fig. 9. Comparison of the distribution system's power losses.

the distribution system for each of the cases in scenario 4 is shown in Fig. 6. As can be seen, it can be inferred that the

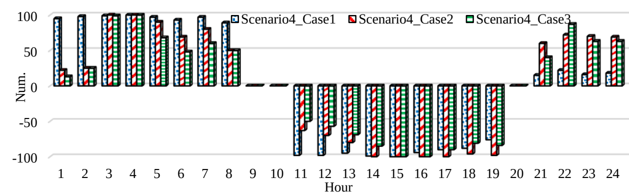

Fig. 10. Optimum number of PEVs in scenario 4.

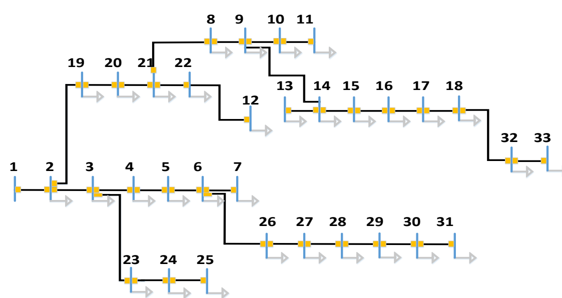

Fig. 11. The distribution system optimal configuration in scenario 4-case 2.

energy interactions between the DSO and PLOs coupled with the reconfiguration process, demonstrates a remarkable effect on load balancing and cost reductions of both PLOs and DSO. Accordingly, the load curve in Scenario 4 has undergone a substantial enhancement compared to Scenario 1.

Technical issues are also impacted sensibly within the scenario 4. The power losses incurred in the distribution system with optimal reconfiguration of the network and presence of the parking lots are illustrated in Fig. 7. Evidently, the power losses across the scheduling periods is noticeably diminished in scenario 4 compared to scenario 1. This reduction in power losses is attributed to two primary factors. First, the strategic reconfiguration and change of paths; and second, optimal management of charging and discharging cycles of PEVs within the parking lot. Fig. 8 depicts the minimum voltage level of the system buses. Specifically, at 15:00, the minimum voltage in scenario 1 is recorded equal to 0.9 p.u.; whereas, in scenario 4, the minimum permissible voltage level is equal to 0.95 p.u. Indeed, the established framework successfully maintains the minimum voltage levels within the distribution system through the opportunities provoked by optimal reconfiguration and parking lots energy interactions.

In an overall comparison of all scenarios, the power losses of distribution system are compared considering the case 3 of overall four scenarios. Results are displayed in Fig. 9. As is evident, there are minimum differences in losses between scenarios 3 and 4. This observation is due to lower impact of parking lot facilities on losses reduction. However, a substantial difference in losses is seen when comparing the scenarios 3 and 4 with those in scenarios 1 and 2. This notice highlights the positive influence of concurrent consideration of reconfiguration and parking lots energy interaction in daily scheduling processes. Fig. 10 depicts the optimal number of PEVs that are handled in scenario 4. Based on this figure, it is inferred that the optimal number of PEVs designated for either charging or discharging, varies across the time intervals at each scenario. For instance, at 07:00 which is identified as a peak charging period, the optimal number of PEVs are computed as 97, 80, and 60. Moreover, in the chosen state with the utmost priority, say as scenario 4-case 2, the reconfiguration process of the distribution system determines the RCS in lines 7, 11, 12, 31, and 37 as open. The optimal configuration of the distribution system, corresponding to this state, is illustrated in Fig. 11. This figure demonstrates that the radial topology of the 33-bus distribution system is kept, to be persistent as an operational constraint of these network.

4. Conclusion

This research focused on developing an interactive operation model for the DSO and PLOs in a smart distribution system. The presented model was intended to enhance both economic and technical goals, leveraging the collaboration of PEV parking lots and system reconfiguration. Additionally, the operational constraints were successfully included in the proposed model. Four different scenarios were explored to assess the performance of the proposed model. The findings showed that the inclusion of parking lot facilities, structural reconfiguration, and the establishment of energy and data interactions between PLOs and the distribution system yielded enhancements in both technical and economic objectives. As different objectives were considered from different participants' points of view, the TOPSIS approach was deployed to reflect the most suitable solution among them. Regarding the solution with the highest priority, the obtained results demonstrated values of 60.3$, 5306.6 kW, and 716.8 kW for the first, second, and third objective functions, respectively. These results demonstrated significant improvements over the base scenario and network operation metrics. The integration of energy interactions between distribution systems and parking lots, facilitated by data sharing, presents promising future opportunities. Areas such as smart parking solutions, demand response programs, resilience and sustainability initiatives, data security and privacy concerns, as well as machine learning approaches, could be further explored here.

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