



Energy Management in Distribution Network with the Presence of Electric Vehicles and Energy Storage Systems Using the Crow Search Optimization Algorithm

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ARTICLE INFO	ABSTRACT
Article History: Received 29 March 2021 Received in revised form 27 May 2021 Accepted 10 June 2021 Available online 10 June 2021 Keywords: Distribution Network, Energy Management, Electric Vehicles, Energy Storage Systems, Renewable Energy Sources, Crow Search Algorithm	Considering the growth in electrical energy consumption and consequently the increasing investment in the distribution sector, as well as the significant portion of losses in the entire distribution network system, operators have been compelled to propose optimal solutions to mitigate these issues. Energy management aimed at reducing consumption and demand is an effective method for load management under peak load conditions and reducing energy consumption, a method that has been employed by several electricity companies for years. Studies conducted on this method are either based on network modeling, which requires precise information about the real-time status of network loads and the percentage contribution of various loads to the total load, or based on data received from measurement devices installed for consumers. In this paper, plug-in hybrid electric vehicles (PHEVs) combined with the integration of renewable energy systems into the power grid offer a promising method to address environmental problems. To this end, a multi-objective algorithm is proposed to optimally locate several renewable energy systems (RES), including parking lots for PHEVs in a distribution system. The proposed algorithm determines the number, locations, and sizes of RES and parking lots. The objective of the proposed algorithm is to minimize the total energy cost of the system. The problem is formulated as an optimization problem solved using the Crow Search Algorithm (CSA), considering power system and PHEV operational constraints. The proposed algorithm is tested on a standard 33-bus distribution system, and the obtained results demonstrate the effectiveness of the proposed method.

1. INTRODUCTION

The distribution system is one of the main components of a power network. If we divide a power network into three main sections: generation, transmission, and distribution, the distribution section, due to its extensive and

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widespread nature, always constitutes one of the costliest parts of a power network. Continuous investments in the design and optimal, reliable operation of this section have made it one of the most expensive parts of the power network. Therefore, numerous designers and engineers are involved in improving and developing this system. Power systems are evolving in response to diverse needs such as higher reliability, loss reduction, optimal operation, and customer service. Moreover, reducing environmental pollution caused by the industry is of great importance. The share of electricity generation in greenhouse gas emissions is 24%. According to forecasts, global electricity consumption will increase by 77% by 2030, and consequently, greenhouse gas emissions will significantly rise [1]. Therefore, effective reduction in greenhouse gas emissions will not be possible without the involvement of the electricity industry. The solution provided by scientists to address this need is the use of distributed generation energy sources. Furthermore, considering the depletion of fossil fuels, countries are increasingly focusing on renewable energy sources. The main aspect of future changes in distribution networks pertains to the emergence of the concept of distribution system management as the central hub for making economic and technical decisions, responsible for supplying the demand load of consumers in an economical and safe manner [2]. Demand Side Management (DSM) as a hardware and software set must make decisions for optimal network operation considering the status of all network components.

The input data for DSM, to perform this decision-making process, is provided through measurement infrastructures and a communication platform. DSM communicates with other subsystems of the control center by executing predetermined functions or programs, evaluates the status of the distribution system, and assists the operator in making intelligent and appropriate decisions [3]. Due to the negative environmental impacts of uncontrolled energy consumption, the use of technologies that help mitigate these negative impacts is continuously advancing. It is predicted that the use of electric vehicles, as one of the technologies aiding in pollution reduction, will significantly expand in the near future. According to a report by the United States Department of Energy (DOE), annual sales of plug-in hybrid electric vehicles (PHEVs) will exceed 300,000 vehicles by 2035. Electric vehicles come in various types, including PHEVs, plug-in electric vehicles (PEVs), and electric vehicles (EVs), which require different energy sources to charge their batteries. In some types of electric vehicles like PHEVs, the battery is charged using the power grid. To charge the battery using the grid, an interface called a charger is used, which primarily converts the grid's alternating current to direct current for battery charging. The charger, in addition to supplying the battery's required power, can also control the power delivered to the grid, where in some types of chargers, only active power is controlled between the grid and the battery, and in other types, both active and reactive power are controlled in both directions, from the grid to the battery and from the battery to the grid. Therefore, the charger plays a significant role in managing power between the grid and the battery [4,5].

In article [6], the development of energy management tools for the installation and operation of photovoltaic (PV) generation, including storage units, provides flexibility to the distribution system operator. This article presents the collection and implementation of these energy management methods, crucial for commercial customers in a microgrid power system. The article defines an energy management system for a microgrid, including advanced PV generators with embedded storage units and a gas microturbine. In article [7], a home energy center model is proposed, which receives electricity, natural gas, and solar radiation at its input to meet the required electricity, heat, and cooling needs at its output. For this purpose, the optimization problem is formulated and solved for three different case studies with the objective of minimizing the total energy cost while considering consumer preferences under optimal temperature and weather conditions. Article [8] proposes a new framework for home energy management (HEM) in the context of renewable-based home energy hubs using a probabilistic optimization method. Consumer energy cost is modeled as an objective of the HEM optimization problem, and various operational constraints of energy hub components are modeled as constraints. The two-point estimation method is included in this article to model the uncertainty associated with the power output from solar panels. Article [9] proposes a distributed framework for demand response and user adaptation in smart grids, where both simulation results and analysis indicate the dynamic behavior and convergence of the proposed algorithm. Based on this algorithm, a new charging method for PHEVs in a smart grid is proposed, where users or PHEVs can adapt their charging rates according to their settings. Simulation results show the dynamic behavior of the charging algorithm and the impact of various parameters on system performance.

Article [10] addresses one of the most challenging issues related to the optimal energy management of smart microgrids, considering multiple and often conflicting objectives. This article models a mixed-integer nonlinear

programming model for optimal energy use in a smart home, considering a meaningful balance between energy savings and comfortable living. Article [11] considers a multi-energy system as an effective pattern for improving energy efficiency and reducing energy supply costs by integrating multiple energy carriers. Energy converters and storage devices with various features are abundant, and the main challenge is how to select the types and capacities of devices, how to connect and manage the selected devices, which is a key challenge for designing optimal structures of new multi-energy systems. The optimal planning problem is formulated as a mixed-integer programming model with the objective of minimizing the overall cost. Three different energy system designs are compared to demonstrate the efficiency and benefits of the proposed planning model. Article [12] presents mixed-integer linear programming (MILP) for the charging and discharging of a large number of PHEVs in a grid-connected charging park. The primary goal of this article is to find the optimal load distribution and reduce the daily charging cost of PHEVs while considering various constraints such as power balance, battery charging and discharging constraints, and PHEV state-of-charge (SOC) constraints.

Article [13] considers PHEVs as an option for energy storage in a smart system that includes renewable energy sources (RES) along with the main grid. The smart charging system ensures that electric vehicle owners charge their batteries during off-peak hours and discharge the remaining energy during peak demand hours. Article [14] develops an energy management strategy for a PHEV. In this case, an optimal rule-based controller selects the appropriate operating mode. Additionally, the advantages and disadvantages of such a vehicle are compared with other vehicles designed by more popular electric power architectures. Article [15] jointly addresses pricing for charging services, scheduling of vehicles owned by PHEV chargers, dropping off reserved vehicles, and managing energy storage in a unified framework that includes key features of practical PHEV charging stations. Based on this framework, an algorithm is developed to find the required parameters for charge management using Lyapunov technique.

In this paper, plug-in hybrid electric vehicles combined with the integration of renewable energy systems into the power grid offer a promising method to address environmental problems. To this end, a multi-objective algorithm is proposed to optimally locate several renewable energy systems, including parking lots for PHEVs in a distribution system. The proposed algorithm determines the number, locations, and sizes of RES and parking lots. The objective of the proposed algorithm is to minimize the total energy cost of the system. The problem is formulated as an optimization problem solved using the Crow Search Algorithm (CSA), considering power system and PHEV operational constraints. The proposed algorithm is tested on a standard 33-bus distribution system, and the obtained results demonstrate the effectiveness of the proposed method. In Section 2, the objective functions and constraints of the problem will be elucidated. Section 3 will focus on explaining the Crow Search Algorithm (CSA) and the methodology for solving the problem. Section 4 will analyze the problem, and finally, Section 5 will present the conclusions drawn from the study.

2. PROBLEM FORMULATION

The primary objective of the proposed CSA-based algorithm is to identify the optimal locations for PHEV parking, PV, wind, and diesel generator units from a specific number of candidate sites in the distribution network. Neither the number nor the locations of DGs are predetermined; instead, they are left for the optimization algorithm to determine. Two different types of parking are considered: commercial and residential garages. The type of parking is determined by its selected location, thus the accessibility plan for PHEVs will vary for each proposed allocation scheme. The charging or discharging schedule of PHEV batteries is determined according to available network resources and the instantaneous SOC of the batteries. The primary goal is to minimize the overall system cost function. This function includes the cost of energy losses from the network, the cost of energy imported from the main grid, the cost of energy supplied by distributed generation units (DGs) from the network, and the cost of energy from the parking lots during battery discharge to support the network. Additionally, maximizing the power supplied from parking lots for charging PHEV batteries is required.

2.1. Objective Function

The objective of the proposed algorithm is to minimize the cost function as follows:

$$\min f = \sum_{t=1}^N [C_{loss} P_{loss}(t) + C_{grid} P_{grid}(t) + C_{UG}(P_{UG}(t)) + C_{DS}(P_{DS}(t)) + C_{PV} P_{PV}(t) + C_W P_W(t) + C_{gr} P_{gr}(t)] \quad (1)$$

where

$$P_{gr}(t) = P_{disch}(t) - P_{ch}(t) \quad (2)$$

$$C_{UG}(P_{UG}(t)) = \sum_{i=1}^{NUG} (a_i + b_i P_{UG-i}(t) + c_i P_{UG-i}(t)^2) \quad (3)$$

$$C_{DS}(P_{DS}(t)) = \sum_{i=1}^{NDS} (a_i + b_i P_{DS-i}(t) + c_i P_{DS-i}(t)^2) \quad (4)$$

2.2. Constraints of the Problem

The first constraint pertains to the power balance limitation such that, in every time interval t , the total power generation must equal the total power demand plus system power losses, as illustrated in equations (5) and (6).

$$P_{DG}(t) + P_{grid}(t) + P_{gr}(t) - P_{loss}(t) - P_D(t) = 0 \quad (5)$$

$$P_{DG}(t) = P_{UG}(t) + P_{DS}(t) + P_{PV}(t) + P_W(t) \quad (6)$$

$$C_{grid} = C_{s1} \quad \forall P_{grid}(t) \leq P_{grid-max} \quad (7)$$

$$C_{grid} = C_{s2} \quad \forall P_{grid}(t) > P_{grid-max} \quad (8)$$

$$SOC_i(t)_{maxmin} \quad (9)$$

$$P_{ch}(t) \leq R_{ch} \quad (10)$$

$$P_{disch}(t) \leq R_{disch} \quad (11)$$

$$SOC_i(t) = SOC_i(t-1) + P_{ch}(t)X(t) - P_{disch}(t)Y(t) \quad (12)$$

$$Y(t) = \begin{cases} 1 & \text{if the batteries are discharging} \\ 0 & \text{if the batteries are not discharging} \end{cases} \quad (13)$$

$$X(t) = \begin{cases} 1 & \text{if the batteries are charging} \\ 0 & \text{if the batteries are not charging} \end{cases} \quad (14)$$

$$X(t) + Y(t) \leq 1 \quad (15)$$

Other operational constraints of the distribution network are similar to those of non-smart distribution networks. Specifically, the voltage must remain within the allowable range, the maximum power flow through the network lines, and the power generation limits of the generators must be observed, as stated in equations (16) to (18).

$$V_{i=1,2,...,nbus} \quad i_{min_i(t)}^{max} \quad (16)$$

$$|S_i(t)| \leq |S_i^{max}| \quad i = 1, 2, \dots, nline \quad (17)$$

$$P_{DG-i} \quad i_{min_{DG-i}(t)}^{max} \quad (18)$$

2.3. Energy Management Plan

According to the available renewable energy sources, such as wind and solar, and considering the availability of PHEVs within parking lots and their SOC levels, energy exchange can be determined. The total hourly generated power includes the available wind and solar power and the maximum power that must be supplied by diesel units,

either owned by the distribution company (UG) or newly established (DS). At any given time, if the available generation, due to resource limitations or failure of one or more sources, is insufficient to support adequate power production, the system relies on other available resources. If these resources are inadequate, the remaining required energy is drawn from the main grid. For instance, in the event of a PV or wind energy source failure, the system will depend on the energy stored in PHEV batteries and the power that can be supplied by diesel generators. If these sources are insufficient, the remaining power is imported from the main grid. However, in the event of a failure of any upstream feeders connecting the network to the main grid, a partial load shedding must be considered, although this scenario is not covered in this paper.

3. CROW SEARCH ALGORITHM (CSA)

A novel metaheuristic method called the Crow Search Algorithm (CSA) was introduced by Alireza Askarzadeh in 2016. This method is based on the intelligent behavior of crows and has been developed to solve optimization problems. CSA is a population-based method, and its main concept is inspired by the theory that crows hide their surplus food in secret locations and retrieve it when needed [16]. The basic principles of this algorithm are as follows:

- a) Crows live in flocks.
- b) Crows remember the locations of their hidden caches.
- c) Crows follow each other to steal food.
- d) Crows protect their caches from potential thieves.

Assume an environment with d dimensions containing a number of crows. The number of crows (flock size) is N , and the position of a crow at each iteration (moment in time) i is represented by the search vector x_i where $x^{i,iter} = [x_1^{i,iter}, x_2^{i,iter}, \dots, x_d^{i,iter}]$. Each crow has a memory that recalls the location where it has hidden its food. At each iteration, the hiding position of the food for crow i is represented by $m^{i,iter}$. This position is the best location the crow has found so far.

Additionally, the crow's memory stores its best-found position. Crows search for more favorable food sources in their surroundings. Assume that at a particular iteration, crow i wants to see the hiding place of crow j . At this iteration, crow i decides to follow crow j to discover its hiding spot. Two scenarios might occur:

1. Crow j is unaware that crow i is following it; hence, crow i learns about the hidden food location of crow j . In this case, the new position of crow i is updated as per equation (19):

$$x^{i,iter+1} = x^{i,iter} + r_i \times fl^{i,iter} \times (m^{i,iter} - x^{i,iter}) \quad (19)$$

where r is a random number in the range $[0,1]$, and $fl^{i,iter}$ is the flight length of crow i at iteration t .

2. Crow j is aware that crow i is following it. In this case, crow j diverts crow i to another location in the search space to protect its food cache. The combined effect of these two scenarios is expressed by equation (20):

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (m^{i,iter} - x^{i,iter}) & \text{if } r_j \geq AP_j^{i,iter} \\ \text{a random position, otherwise} \end{cases} \quad (20)$$

where r is a random number in the range $[0,1]$, and $A_j(t)$ is the probability of awareness of crow j at iteration t .

The implementation process of the Crow Search Algorithm involves the following steps:

1. Initialize the problem parameters and set adjustable parameters.
2. Assign initial positions and memories to the crows.
3. Evaluate the objective function value.
4. Generate new positions.

5. Check the feasibility of new positions.
6. Evaluate the objective function value at new positions.
7. Update memory.
8. Check the termination criterion of the algorithm.

The advantages of the Crow Search Algorithm include ease of implementation, simple understanding, avoidance of local optima, and high convergence speed.

4. SIMULATION RESULTS

This section presents the simulation results for the placement of electric vehicle parking with solar, wind, and diesel generator units in 33-bus distribution networks, aiming to improve the characteristics of distribution network power using the Crow Search Algorithm (CSA). Simulations have been evaluated in both the base state, without the use of distributed generation and electric parking (base state), and with the deployment of these resources.

4.1. System Under Study

The standard IEEE 33-bus network has been selected for implementing the proposed method along with the energy management system. The mentioned networks have been utilized to implement the location of electric parking along with distributed generation, including solar arrays and diesel units. Figure (1) shows the single-line diagram of the 33-bus network.

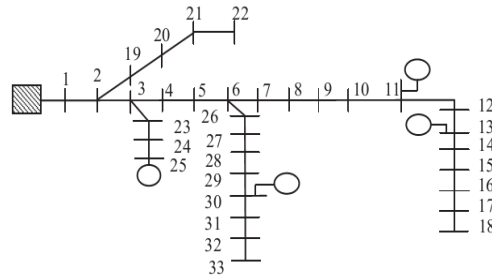


Fig.1. Single-line Diagram of the 33-bus Network

A 24-hour simulation period has been considered in this study. Figure (2) illustrates the availability and presence of vehicles in commercial and residential parking lots. It is assumed that the initial SOC or battery charge levels of the vehicles in the parking lots are as shown in Table (1). The minimum and maximum allowable SOC for vehicle batteries are defined as 25% and 90%, respectively. The nominal capacity of vehicle batteries is 16 kWh, and the maximum charging and discharging rates of these batteries are considered to be 2.3 kW.

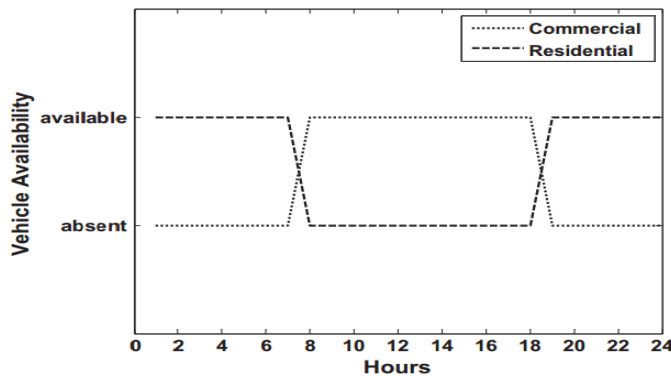


Fig. 2. Vehicle Presence in Parking Lots over 24 Hours

Table 1. Initial Battery Charge Levels in Parking Lots

Primary SOC Percentage	30	45	70
Number of Vehicles (%)	25	25	25

For the purpose of simulation and assessing the optimization method's efficiency and energy management effectiveness, the solar radiation and wind speed levels for May have been considered for the simulation, with the average values used accordingly. The average wind speed and average solar radiation are depicted in Figures (3) and (4), respectively.

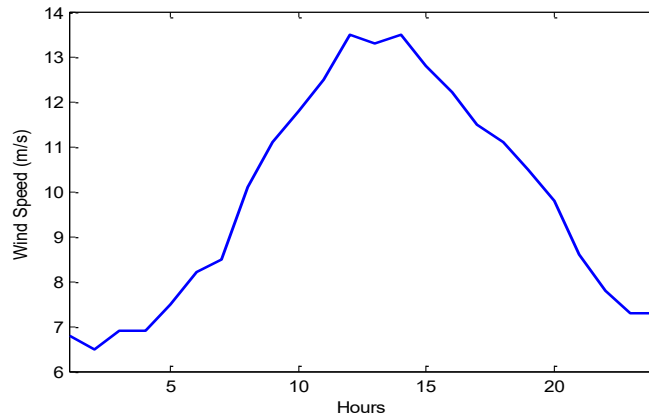


Fig. 3. Average Wind Speed at Different Hours

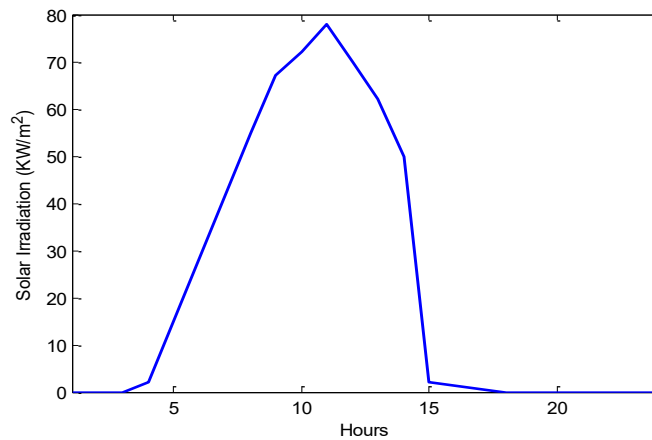


Fig. 4. Average Solar Radiation at Different Hours

The considered wind turbine is an AC wind turbine with a nominal power of 1500 kW. The power curve of this wind turbine at different wind speeds is shown in Figure (5). The studied solar panels are polycrystalline type, model GEPV-200, each with a nominal power of 200 W. The output power of the solar panels is assumed to have a linear relationship with solar radiation.

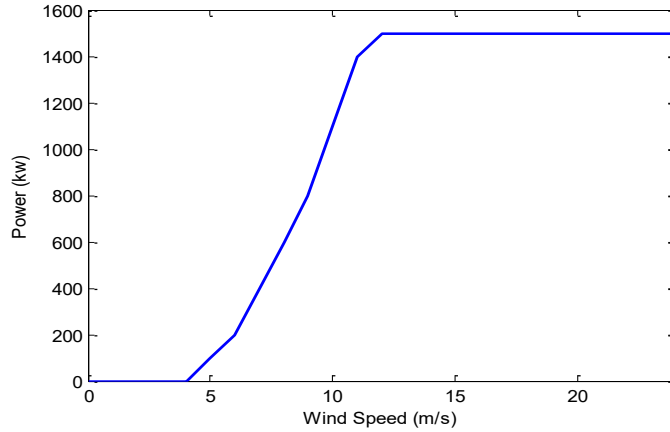


Fig. 5. Wind Turbine Power Output at Different Wind Speeds

Considering geographical structure and environmental constraints, the installation of distributed generation or parking cannot be done at any desired location, and suitable locations for different types of DG installation at each bus have been determined. Table (2) presents the buses where DG or PHEV installation is possible. These buses are considered as candidate locations for DG or charging parking installation in the algorithm. Charging stations are selected in busy areas with high traffic. In these regions, the central government also has adequate and suitable land for building parking and high-capacity charging stations.

4.2. Simulation Results for the Base State

In the base state, the network's voltage profile at peak load conditions and the most severe voltage deviation are depicted in Figure (6), showing that the minimum network voltage is 0.9134 per unit at bus 18, which is outside the allowable voltage range.

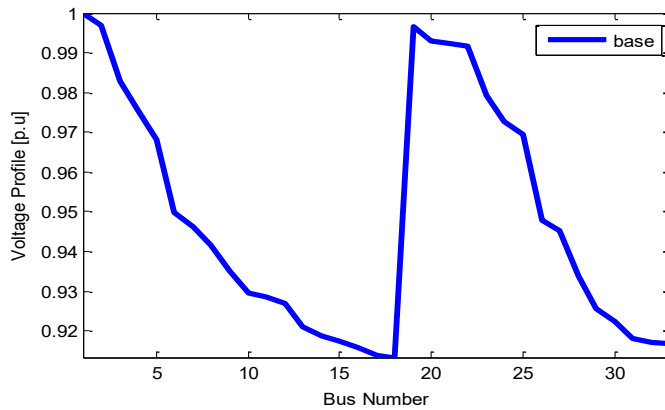


Fig. 6. Voltage Profile of the 33-bus Network in the Base State

Additionally, the network loss curve over the 24-hour peak load period is shown in Figure (7). As observed, the maximum active power loss in the base state without any distributed generation and charging parking is 201.9 MW.

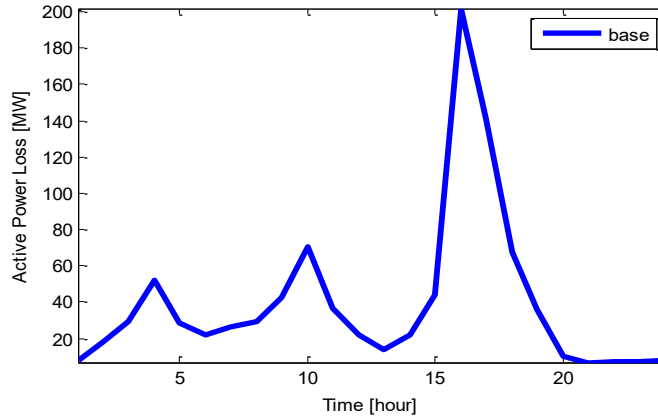


Fig. 7. Network Loss Curve in the Base State of the 33-bus Network

4.3. Simulation Results with the Deployment of Parking and Distributed Generation

This section presents the results of the location of distributed generation and electric parking with the objective of minimizing system costs using the CSA. The maximum power of each solar array in the 33-bus network is 200 kW, and there is a linear relationship between output power and solar radiation. In this study, three solar array units with a maximum capacity of 600 kW are used. Table (2) lists the candidate buses for installing solar arrays, diesel generators (DS), and electric parking.

In the 33-bus network, a maximum of four 200 kW diesel generators can be installed. Electric parking can have a maximum of eight commercial and residential parking lots, as shown in Table (2).

Table 2. Candidate Buses for Installing Distributed Generation and Electric Parking in the 33-bus Network

Shin Candidate	6	8	29	30	27	13	10	-
Type DG	PV	PV	PV	DS	DS	DS	DS	-
Shin Candidate	24	21	31	32	28	17	15	12
Parking Type	G_C	G_C	G_C	G_R	G_C	G_C	G_R	G_R

The CSA method achieved a lower cost in solving the problem of deploying distributed generation and electric parking, amounting to 0.43751 million dollars. In the proposed method, two PV units are installed in buses 8 and 29 with capacities of 130 and 165 kW, respectively. Additionally, five parking lots are installed in buses 12, 17, 28, 31, and 21 with 1223, 319, 1300, 863, and 819 vehicles, respectively, in the 33-bus network. As observed, the proposed method does not utilize DS diesels for load supply, which is an advantage of the proposed method, focusing on clean energy production.

After applying the proposed algorithm results to the 33-bus network, the network was examined for power loss and voltage over the 24-hour peak load period. In the base state, the total network loss over 24 hours was 950.39 kW, which, after optimization, was reduced to 688.92 kW over 24 hours, indicating a 27.51% reduction. The active power loss over 24 hours is depicted in Figure (8). The highest loss occurs at hour 16, reducing from 201.9 kW to 171.4 kW, showing a 15.10% improvement.

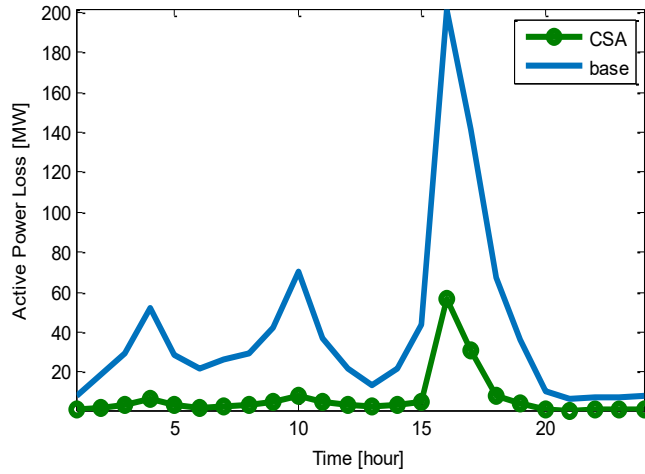


Fig. 8. Power Loss Curve Over 24 Hours Before and After Optimizing the 33-bus Network

Without utilizing distributed generation and electric parking in the 33-bus network, during hours 4, 10, and 16 of the day, the voltage drops significantly and falls outside the allowable range. After optimal deployment of solar arrays, diesel generators, and electric parking, the voltage remains within the allowable range throughout the day, with the minimum voltage rising from 0.9134 per unit to 0.9202 per unit.

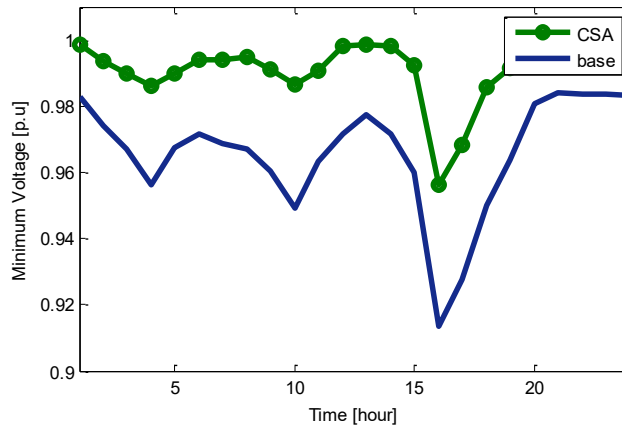


Fig. 9. Minimum Voltage Profile Curve in the 33-bus Network for Optimized and Base States

Figure (9) shows the minimum voltage curve over 24 hours. Moreover, in the worst conditions occurring during peak load at hour 16, the voltage profile of the network's buses is depicted in Figure (10). As seen, after optimization, the voltage profile becomes smoother, and the network's condition significantly improves. Figure (11) presents the purchased power from the upstream network. Before optimization, in 71% of the hours, the allowable maximum power received from the main feeder (1.110 MW) was not adhered to, and all network loads and system losses were supplied from the main feeder. After optimization and the installation of distributed generation sources and the energy management of electric vehicle parking, only at hour 16 was the allowable maximum power received from the feeder exceeded, corresponding to the network's peak load condition.

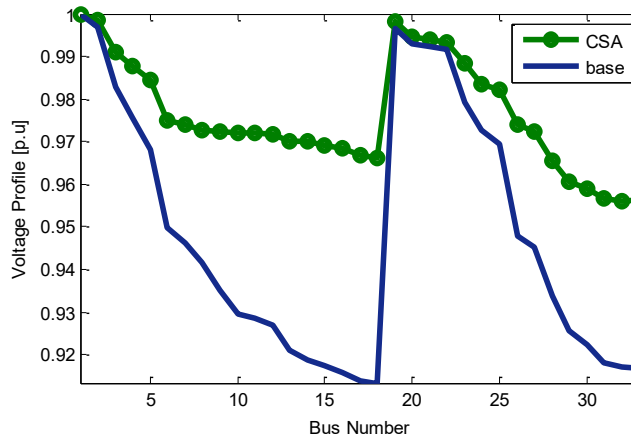


Fig. 10. Voltage Profile of Network Buses During Peak and Worst Conditions of the 33-bus Network

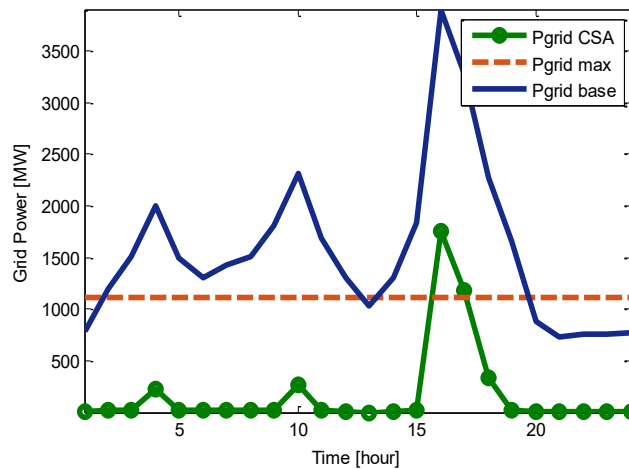


Fig. 11. Power Received from the Main Feeder Over 24 Hours of the 33-bus Network

In the optimized state, some network loads are supplied by distributed generation sources and electric vehicle parking, with the remainder supplied from the main feeder. Figure (12) depicts the power curve of solar arrays and wind turbines over 24 hours. Solar arrays generate power during the midday hours and do not produce power for 60% of the day.

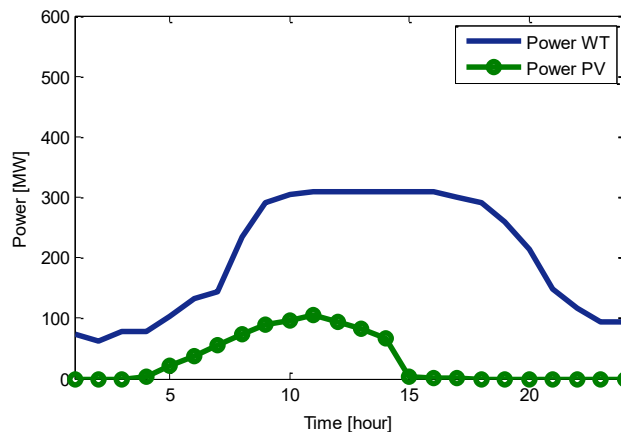


Fig.12. Power Output of Solar Panels and Wind Turbines at Different Hours in the 33-bus Network

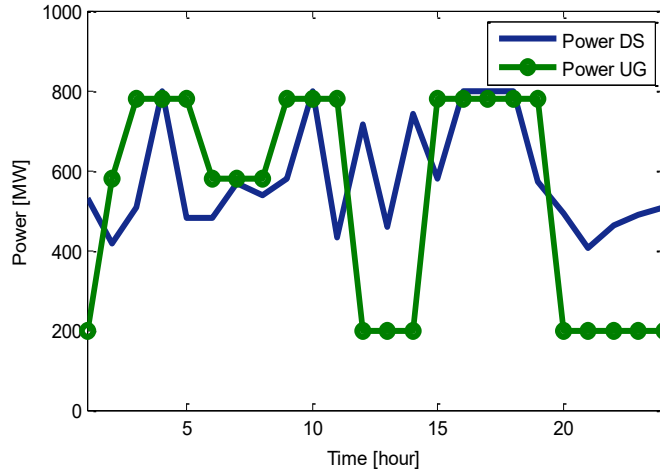


Fig.13. Power Output of DS and UG Diesel Generators in the 33-bus Network

When the power of solar arrays cannot meet the load demand, diesel generators are activated and inject power into the network. Figure (13) shows the power output of DS and UG diesel generators. UG diesels have a maximum of 780 kW, and according to the results obtained from the CSA method, the power generated by DS diesels is zero.

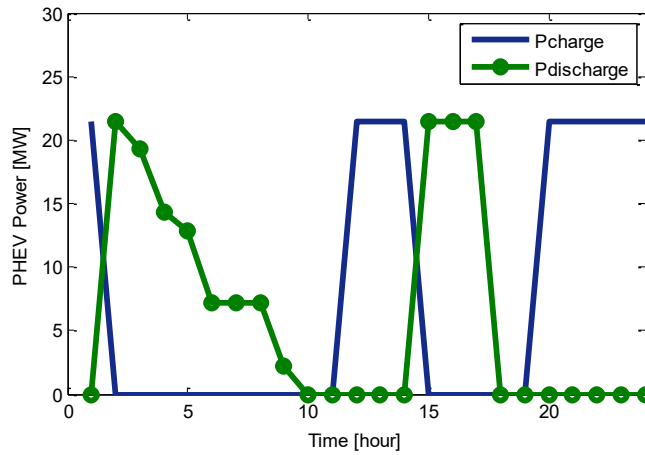


Fig.14. Charging and Discharging Power of Vehicles in PHEV Parking Lots in the 33-bus Network

In Figure (14), the charging and discharging curve of electric parking lots is depicted. Considering the various network conditions, vehicle charging and discharging occur at different times. During the peak consumption hour (16:00), the parking lots act as a distributed generation source, discharging and producing power until 19:00, when the vehicle battery charge reaches its minimum. After 19:00, as the network load decreases, the electric parking lots are recharged.

5. CONCLUSION

This paper presents an enhancement in the power quality of the distribution system by considering distributed generation resources and electric vehicles, with the objective of minimizing energy production costs using the novel Crow Search Algorithm (CSA). Specifically, this study optimizes the placement of distributed generation resources and electric vehicle parking lots in the distribution network. The distributed generation resources employed in this study include solar units, wind units, and diesel generators. The objective function is to minimize the overall system costs, which include the cost of network energy losses, the cost of energy injected by the main network, the cost of energy supplied by distributed generation resources, and the cost of energy supplied by electric vehicle parking lots during battery discharge to support the network.

The constraints of the problem include the power production and consumption balance constraint, network energy cost constraint, parking battery constraints (including storage capacity, charge rate, and discharge rate), and network constraints (including bus voltage limits, line thermal limits, and generation capacity limits). The CSA determined the optimal locations for distributed generation resources and electric vehicle parking lots. This study considered two types of parking lots: commercial and residential. The type of parking lot was determined based on its selected location. Consequently, the accessibility pattern of electric vehicle parking for each proposed site plan was considered different. Additionally, this study established a charging/discharging schedule for electric vehicle parking batteries according to the available network resources and battery charge profiles.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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