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The Optimal Parking Lot for Electrical Vehicle: An Assessment Based on Artificial Immune System Algorithm

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Abstract— *The optimum location of electric vehicle (EV) parking lots is critical in distribution network design for lowering costs, boosting revenues, and enhancing dependability. However, conventional distribution network schedulers were not designed with these variables in mind. Furthermore, the increased use of EVs for environmental reasons mandates the planning of EV parking spaces. As a result, distribution network designers must examine network technical difficulties, design approaches, and changing consumer needs. The placement of dispersed manufacturing resources and EV parking without sufficient planning and ideal location leads in economic challenges for investors and technical concerns for the network. As a result, future distribution networks should prioritize the ideal placement of EV parking lots and distributed production resources in order to maximize network capabilities and meet the needs of companies and power applications in the digital society. According to the findings, the rate of EV parking installations is very high. When power consumers remain connected to the grid during peak hours, distribution businesses benefit significantly, and the overall voltage profile improves. Variations in electric vehicle (EV) battery capacity, power cost, EV adoption, and the weighting coefficients required for optimization will all have different outcomes. It is critical to precisely determine the battery capacity of electric vehicles (EVs) as well as the efficiency of inverters in order to produce more accurate results. According to the findings, increasing the number of parking lot for EVs in a network enhances the benefit from minimizing losses, and providing peak load significantly. So that using 2 parking lot for EVs in a network can increase the overall profit to 129%.*

Keywords—Electric vehicles, optimization, parking lot, artificial immune system algorithm, optimal location.

1. INTRODUCTION

The electric vehicles (EVs) concept was first introduced to the network with the presentation of the model, and the cost was used in the direction of the company in the regulation market and the side services market [1–5]. On the other hand, because connecting an EVs to the grid has little effect on the power grid, EVs have been introduced as distributed energy sources in the electric energy market in some studies by introducing a new actor called the aggregator, which encourages car owners to connect to the grid while maintaining and establishing a relationship between the independent user of the system and the car owners [6–11]. Due to the limited electrical capacity of the cars in Barghada, they have no effect on the network; thus, in these studies, parking lots with equipment that The ticket provide network connection for the vehicle by placing the number of In terms of the vehicle itself, the role of vehicle-to-grid as well as frequency regulation has been investigated in the field [12–18]. A study on the optimal charge profile to increase consumption during off-peak hours was conducted Yu [19], and Clement-Nyns et al. [20] investigated the effect of the charge profile on the distribution network. In general, most research in the field of EVs focuses on optimal charging planning in order to achieve the desired level of various indicators, such as losses and voltage profiles. Furthermore, using the technology of connected cars as a storage system has focused on the parking location of connected cars, taking into account the limitation of losses and reliability as an economic limitation [21]. There are also studies on the presentation of the charging algorithm that can increase the load in providing fewer hours, which has been completed. The charging schedule for EVs is a common theme, and due to the indecisiveness of EV owners, it is possible that they will not participate [22]. Drops and reductions in the battery life of an EV as a result of irregular and consecutive charging and discharging are not always economically and technically feasible [23].

One of the most important goals of distribution network design is to reduce costs while increasing revenues, as well as to reduce losses while improving reliability, which are two important factors in distribution network design and the location of production resources. The distribution network scheduler has not been considered based on these factors. Is furthermore, with the growing use of EVs for bio-environmental reasons, the need for planning for the construction of EV parking lots is obvious.

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As a result, designers of distribution networks should consider technical issues of the network, design approaches, and use the network in accordance with the new needs of these consumers. The placement of dispersed production resources and EV parking in the distribution network without technical planning and optimal location results in economic problems for the parking investor and technical problems for the profit [24]. There is a distribution network in place. The location of these two main elements of future distribution networks is based on making better use of the network's capabilities for the needs of industries and electricity applications in the digital society.

The positioning of distributed generation resources and electric vehicle (EV) parking within the radio distribution network was investigated in this study. A resource source in the field has been identified: The one cultivated in the field. The labor used by the companies to manufacture the fabric. With parking lots and dispersed production resources, this study attempted to optimize the existing distribution network so that the investor could guarantee complete EV parking at the lowest possible cost. Nonetheless, the distribution network vector will strive to minimize losses as much as possible. The income generated by EV parking to provide peak load, the cost of establishing the parking lot, the cost of charging cars in the EV parking lot to provide peak load, and the cost of charging EVs for driving purposes are all factors that influence the optimal location of the EV parking lot. Version 1 of this model was loaded with heavy and light loads using a multi-objective function to optimize the placement of electric vehicle (EV) parking spaces on a standard 13-bus system. The optimal parking problem for electric vehicles was solved using the nervous system's artificial immune system algorithm (AISA).

2. MATERIALS AND METHODS

This section provides an explanation of the research overview process. The subsequent section elucidates the process of modeling the allocation of EV parking spaces in relation to the distribution of dispersed production sources, taking into account the preferences of the parking investor.

The parking investor's decision-making index for selecting three potential locations for bus construction is determined by evaluating the reliability indicators, namely land price and the number of users connected to each bus (bus attractiveness index). Parking refers to the utilization of the distribution network. Subsequently, the computation of the power output and the determination of the quantity of individuals in attendance within the parking area are conducted utilizing the probabilistic model. The distribution company selects appropriate parking and distributed generation (DG) points by minimizing losses, taking into account the input from the parking investor and the model's output regarding the number and capacity of DGs to be installed in the network. During this phase, the algorithm for the artificial security system is employed to address the optimization problem. Fig. 1 illustrates the procedural outline of the distributed generation and EV parking location problem investigated in this study.

2.1. Probability modeling of EV parking

The first parameter is the expected travel distance. It was employed a log-normal distribution to model the distance each vehicle traveled. This distribution's random variable N is generated using the standard normal distribution of random numbers [25]. The first equation explains how to generate N random variables.

$$N=\sqrt{-2\cdot\ln\left(U_1\right)}\times\cos\left(2\pi U_2\right). \tag{1}$$

Where U_1,U_2 are random variables with independent uniform distributions in the interval and N(0,1] is a random variable with a mean of zero and a variance of one. The expected distance traveled based on statistical data is represented by Eq. (2).

$$M_d=e^{(\mu_m+\sigma_m\cdot N)}. \tag{2}$$

Where μ_m and σ_m are the parameters of the log-normal probability distribution and M_d is the expected distance traveled by the EV. Using Eq. (3) and the mean and standard deviation of the statistical data extracted from the distance traveled by EVs, the log-normal distribution parameters are computed.

$$\left\{\begin{array}{l}\mu_m=\ln\left(\frac{\mu_{md}^2}{\sqrt{\mu_{md}^2+\sigma_{md}^2}}\right)\\ \sigma_m=\sqrt{\ln\left(1+\frac{\sigma_{md}^2}{\mu_{md}^2}\right)}\end{array}\right.. \tag{3}$$

Where μ_{md} and σ_{md} are respectively the mean and standard deviation of the distance traveled by EVs based on statistical data. The second parameter that affects the performance of the EV and the amount of charging demand is the energy consumption over the distance traveled. This parameter is calculated according to Eq. (4).

$$\mathrm{E_m}=\mathrm{a}\cdot\mathrm{k_{EV}^b}. \tag{4}$$

Where E_m represents the energy consumption, a represents the constant EV energy consumption, and b represents the constant EV energy consumption. The ratio of electric energy to the total energy consumption of the EV is represented in kV, and in this study its value has been set to 1.

The maximum distance that can be covered when the battery is fully charged is calculated from Eq. (5).

$$\mathrm{M_{dmax}}=\frac{\mathrm{B_{CAP}}}{\mathrm{E_m}}. \tag{5}$$

Where B_{CAP} is the battery capacity of the EV in kilowatt hours and M_{dmax} is the maximum distance that can be covered with a full charge of the battery. The demand for car energy charging (E_{demand}) is also calculated from Eq. (6).

$$\mathrm{E_{demand}}=\left\{\begin{array}{ll}\mathrm{B_{CAP}} & ;\mathrm{M_d}\geq\mathrm{M_{dmax}}\\ \mathrm{M_d}\cdot\mathrm{E_m} & ;\mathrm{M_d}<\mathrm{M_{dmax}}\end{array}\right.. \tag{6}$$

In the third parameter, the probability of cars arrival and departure the parking lot is used to calculate the expected time for the presence of an EV. Entry and exit times are calculated based on the probabilities of a Gaussian distribution. This distribution is the most accurate predictor of the behavior of private automobile drivers. Based on statistical data, Eq. (7) is used to calculate the probable arrival and departure.

$$\left\{\begin{array}{c}\mathrm{t_{arrival}}=\mu_{\mathrm{arrival}}+\sigma_{\mathrm{arrival}}\cdot\mathrm{N_1}\\ \mathrm{t_{departure}}=\mu_{\mathrm{departure}}+\sigma_{\mathrm{departure}}\cdot\mathrm{N_2}\end{array}\right.. \tag{7}$$

where $\mu_{arrival}$, $\sigma_{arrival}$, and $t_{arrival}$ represent the mean, standard deviation, and estimated arrival time of an EV to the parking lot. $\mu_{departure}$, $\sigma_{departure}$, and $t_{departure}$ are the respective mean, standard deviation, and probable time of departure. The rise of EV in parking lots and N_1, N_2 Using random variables with a mean of zero and a standard deviation of one, the arrival and departure must satisfy the $t_{departure}$ > $t_{arrival}$ constraint. The Eq. (8) is used to calculate the expect time ($t_{duration}$) for the presence of the car in the parking lot.

$$\mathrm{t_{duration}}=\mathrm{t_{departure}}-\mathrm{t_{arrival}}. \tag{8}$$

Based on the waiting time for the presence of the car in the parking lot and the expected distance traveled by the car, the

Table 1. Vehicle class parameters.

Vehicle class	$B_{CAP}(kWh)$	a $\left(\frac{kWh}{mile}\right)$
1	10	0.38
2	12	0.43
3	16	0.57
4	21	0.82

expected charge level is calculated. The probable desired charge level ($SOC_{desired}$) is calculated from the Eq. (9).

$$SOC_{desired} = Min\left\{\left[SOC_{init} + \frac{E_{demand}}{B_{CAP}}\right], \left[SOC_{init} + \frac{t_{duration} \cdot chr}{B_{CAP}}\right]\right\}. \tag{9}$$

Where chr is the rate of charge and SOC_{init} is the initial level of charge. For the modeling of EV parking, four car classes with varying market shares are considered. The characteristics of this class of automobiles are shown in Table 1. It is important to note that index b is ineffective because cars can only run on batteries and cannot use fossil fuel.

2.2. Parking lot best location for investors

In this section, the parking investor's decision is modeled based on three factors: reliability, land cost, and expected acceptance rate, and three candidate points for each EV parking lot are introduced to the distribution network operator.

- Realiblity Index

To expedite the evaluation of the dependability of various buses for parking construction, a reliability index has been established for each bus. The assessment of the dependability of various buses for parking construction is expedited by evaluating the average shutdown time index. This indicator is entirely predicated on the electrical spatial positioning of the bus. Initially, the index is computed for each individual bus, followed by its normalization using the maximum value that has been chosen. To calculate this index, the relationship between λ and r equation for series and parallel elements was used. The average off time is calculated from Eq. (10). λ_i indicates the failure rate of the i-th bus equivalent, ri the repair time of the i-th bus equivalent, the average bus AIT_i of the off-time of the i-ohm bus, and the average AIT_i^{bus} of the normalized off-time of the i-th bus. This index, which is a number between zero and one, is one of the factors influencing the decision of the parking lot investor.

$$\mathrm{AIT}_i^{Bus} = \frac{\mathrm{AIT}_i}{\mathrm{Max}\left\{\mathrm{AIT}_j\right\}} = \frac{\lambda_i r_i}{\mathrm{Max}\left\{\mathrm{AIT}_j\right\}}. \tag{10}$$

- Buses attractiveness index for the parking lot

This index is calculated from the weighted sum of the number of household, commercial, and industrial passengers in each bus and dividing this sum by the weighted sum of all passengers. This index has a direct correlation with the number of passengers present in each bus for parking is calculated. The value of all indices is then standardized based on the most obtained index. The Eq. (11) describes the calculation of the bus attractiveness index.

$$\mathrm{BAI}_i^{Bus} = \frac{\frac{\left(\alpha\times n^{\mathrm{i}}_{\mathrm{residential}}\right)+\left(\beta\times n^{\mathrm{i}}_{\mathrm{commercial}}\right)+\left(\gamma\times n^{\mathrm{i}}_{\mathrm{industrial}}\right)}{\left(\alpha\times n^{\mathrm{total}}_{\mathrm{residential}}\right)+\left(\beta\times n^{\mathrm{total}}_{\mathrm{commercial}}\right)+\left(\gamma\times n^{\mathrm{total}}_{\mathrm{industrial}}\right)}}{Max\left\{BAI_j^{Bus}\right\}}. \tag{11}$$

Where α, β, and γ are the weighting coefficients for rating residential, commercial, and industrial subscribers, $n^i_{customergroup}$ is the number of subscribers of each group in different buses, and $n^{total}_{customergroup}$ is the total number of subscribers of each group in the bus. BAI_i^{Bus}, which also shows the bus attractiveness index for i-th bus.

- Land cost

This index includes only the cost of purchasing land for a parking lot's construction. Other costs, including the cost of purchasing electricity from the network, the cost of parking, and the cost of charging equipment for EVs, are identical for all buses. For the purpose of calculating this index, the standard index of land cost was considered for each item. This indicator of the land price distribution in the geographical area of the bus under study is the geographical maximum; it is defined and calculated using Eq. (12) for the set of buses of each feeder.

$$PC_i^{bus} = \frac{LC_i^{bus}}{Max\left\{LC_j^{bus}\right\}}. \tag{12}$$

Based on the three introduced indicators, Eq. (13) is used to calculate the parking investor's decision-making index for each bus.

$$\begin{aligned}&\mathrm{PIDMI}_i = \left(\eta_1 \times AIT_i^{Bus}\right)\\ &- \left(\eta_2 \times BAI_i^{Bus}\right) + \left(\eta_3 \times PC_i^{Bus}\right).\\ &\eta_1, \eta_2, \eta_3 \geq 0\end{aligned} \tag{13}$$

Where, the defined coefficients η_1, η_2, η_3 have been taken into account to apply the restrictions of the investor.

2.3. Optimization algorithm

The presumptive architecture of the smart grid enables the power system operator to analyze and monitor the distribution network using measurement instruments and smart grid infrastructure [26]. According to the infrastructure and structure of the intelligent distribution network, the operator can define and optimize a variety of objective functions.

The immune system is an intelligent system that protects the body from antigens, also known as toxins and foreign substances. When an antigen enters the body, it stimulates the immune system to produce the appropriate antibody to defend against it. An intelligent, antigen-optimized procedure is required to generate the appropriate antibody. The algorithm for the artificial immune system is a proposed optimization algorithm based on a mathematical model of appropriate antibody production. Although this algorithm shares similarities with the genetic algorithm, it appears to be more effective at locating the global optimal point. Transcendence and correction of the receiver are two essential security system features. By utilizing the memory function of this algorithm, they contribute to the evolution of new antibodies with a higher affinity for combining with antigens than the previous antibodies. Both permutation and the mutation operator in the genetic algorithm introduce random changes to the search space to increase its diversity. But their difference lies in the modification rate, which depends on the combination of antigens. In general, antibodies with low antigen-combination affinity are more prevalent than antibodies with high antigen-combination affinity. This phenomenon, which governs the process, is known as correction. This operator is represented by the Eq. (14) [27], [28].

$$X = X + \left(\beta \cdot e^{-f*}\right) \cdot N\left(0, 1\right). \tag{14}$$

Where X is the true value of the variables of an antibody, β is a constant rib for the mutation step that is usually chosen between zero and one, f∗ is the normalized value of f (antibody fitness value), and N(0,1) is a random value that follows the normal probability density function with a mean of zero and a standard deviation of 1. The value of f∗ is obtained from Eq. (15).

Where f_{max} and f_{min} represent the maximum and minimum merit values for this generation, respectively. In fact, with this normalization, we attribute a value between zero and one to every antibody. This normalized ability will equal zero for antibodies with lower ability and one for those with greater ability. As is evident from Eq. (14), the mutation step for a creature with a greater anti-wind ability will be smaller.

$$f* = \frac{f - f_{\min}}{f_{\max} - f_{\min}}. \tag{15}$$

Using the proposed algorithm, there is no specific criterion for terminating an optimization program. Depending on the operator's identification, the algorithm completion criterion may be the program's execution time, the number of algorithm repetitions, or the maximum value of the objective function. The time criterion indicates that the program will terminate after a certain amount of time has passed since the execution of this algorithm. Regarding this criterion, it should be noted that if only a brief amount of time is considered, it might be reached out the end of the algorithm before obtaining the desired result. In the maximum value criterion, the program terminates when an answer is discovered for which the value of the calculated objective function is less than the specified value [29], [30]. In this study, it is considered both the number of optimization loop iterations and the maximum objective function value.

AISA is a computational technique inspired by the natural immune system's processes and mechanisms. Modeled after the human immune system, which defends the body against harmful pathogens, the AISA applies principles such as pattern recognition, learning, and memory to problem-solving in various domains. This algorithm employs a decentralized and distributed approach, mimicking the way the immune system operates with a vast network of interacting agents.

AISA involves the creation of artificial antibodies that represent solutions to a given problem. Through processes like affinity maturation and clonal selection, the algorithm refines these antibodies based on their effectiveness in addressing the problem at hand. The AISA adaptability and self-regulation make it particularly suitable for dynamic and complex environments, where it can continuously evolve and improve its performance over time. The algorithm's inspiration from the immune system provides a unique perspective on problem-solving, contributing to its effectiveness in addressing complex and dynamic challenges across various fields.

3. RESULTS AND DISCUSSION

In this section, we present and compare simulation results for a 13-bus distribution system under two distinct scenarios, aiming to conduct a detailed analysis. Fig. 1 illustrates the configuration of the investigated network, while Table 2 outlines the characteristics of the distributed loads. For the EV parking lot integrated into the distribution network, specific criteria are applied in the simulations. During off-peak hours, Electric Vehicles (EVs) are mandated to receive 20% of their battery capacity from the network, returning 10% each hour during two peak hours. The network load varies across three levels: low, medium, and high. In the simulation model, the parking lot is represented as a bus with no reactive power, exhibiting negative active power during charging and discharging modes. The buses designated for connection to the EV parking lot are depicted in Fig. 1, with a total fleet size of 120 cars.

Fig. 2-a portrays the hourly variations in the number of vehicles parked in the lot over one year for a fleet of 120 EVs. Notably, EVs predominantly remain in park mode during this period. For a more focused analysis, Fig. 2-b illustrates the number of EVs parked over 120 hours. Furthermore, Fig. 2-c displays the clustered production power of the EV fleet for 120 consecutive hours, derived from Fig. 2-a. The fleet's power output is categorized into discrete states of 0.00 MW, 0.20 MW, and 0.40 MW, corresponding

Table 2. Distributed loads on IEEE 13 node test feeder.

Node	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-3 kVAr
634	Y-PQ	160	110	120	90	120	90
645	Y-PQ	-	-	170	125	-	-
646	D-Z	-	-	230	132	-	-
652	Y-Z	128	86	-	-	-	-
671	D-PQ	385	220	385	220	385	220
675	Y-PQ	485	190	68	60	290	212
692	D-I	-	-	-	-	170	151
611	Y-I	-	-	-	-	170	80

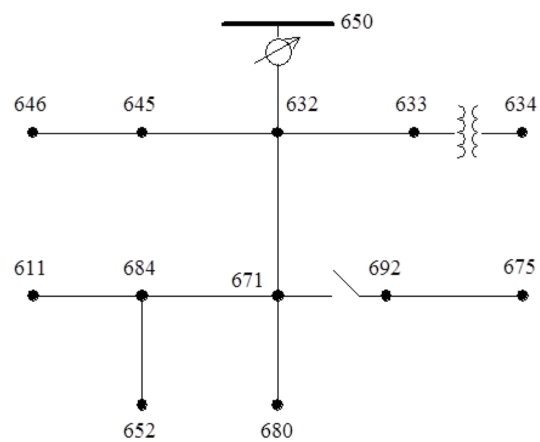

Fig. 1. IEEE 13-buses test feeder scheme.

to the powers generated by a fleet of EVs with a maximum production power of 4.00 MW. This detailed examination provides insights into the nuanced dynamics of the EV fleet's contribution to the distribution system under different load conditions.

To facilitate the analysis of the simulation outcomes, two distinct scenarios have been taken into account, both of which will be thoroughly examined in the subsequent sections.

3.1. Scenario 1

The constraints imposed by lines, transformers, and parking management intricacies preclude the establishment of a singular, extensive charging and discharging area for Electric Vehicles (EVs). Consequently, three network buses (646, 611, and 608) were identified as potential parking locations in this study. Under this scenario, EV parking lots with varying penetration levels (100%, 70%, and 30%) are integrated into the network for a duration of one year, spanning both peak (12 p.m.) and off-peak (3 p.m.) hours. A penetration level of 100% signifies the full participation of all EVs in the lot during that hour. Fig. 3 illustrates the network load curve, contrasting scenarios without EV parking and with a 120 EV penetration level.

With 100% and 70% penetration level, the ultimate profit resulting from EV parking installations amounts to $1,418,950 and $1,044,911, respectively. This represents a decrease in final profit compared to a 100% automobile penetration scenario. The optimization problem details are outlined in Table 3. Notably, at 100% and 70% penetration levels, the optimal number of EV fleets remains consistent, but the gains in terms of loss reduction, enhanced reliability, and peak load provision are more pronounced with a 100% EV penetration. Conversely, at a 30% EV penetration, the optimal number of EV fleets increases, yet the benefits associated with loss reduction, reliability improvement, and peak load provision exhibit a significant decline. Hence, the overall advantage is contingent upon the level of EV penetration in the parking lot. It underscores the importance of devising ample

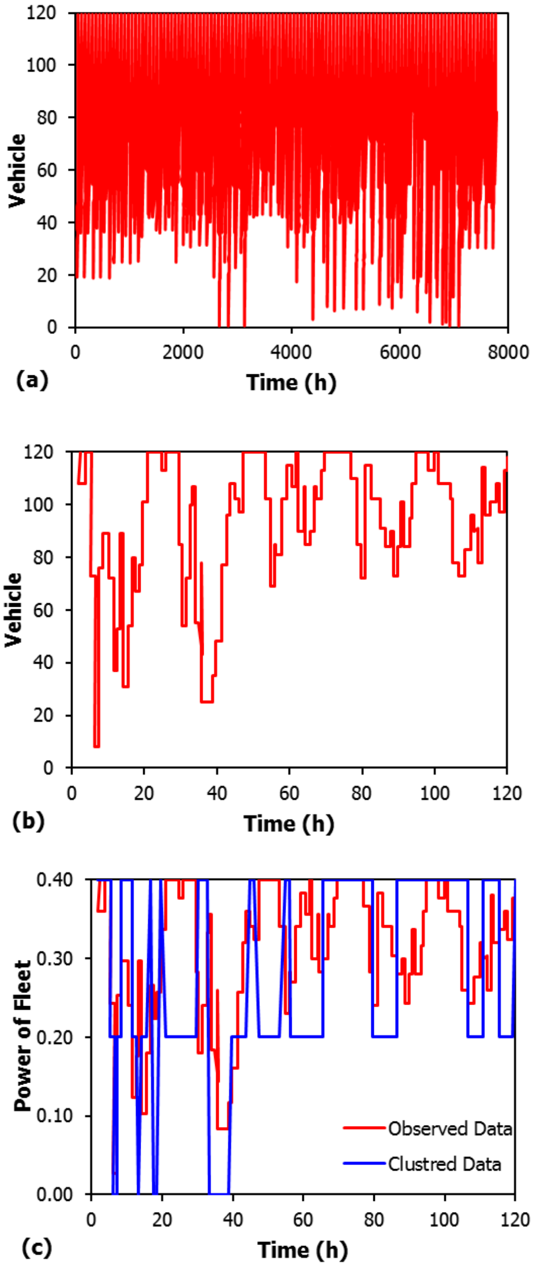

Fig. 2. a) Hourly data of the number of vehicle parked in the parking lot b) Number of vehicle parked in the parking lot during 120 hour, c) The power of the fleet of electric vehicles.

incentives to encourage EV owners to utilize EV parking lots during peak hours.

Fig. 4 illustrates the voltage profile delivered to the distribution network by the EV parking lot at peak load and with a 100% EV penetration. Evidently, the voltage profile of specific buses experiences an enhancement, validating the positive impact of EV parking lots on the distribution network's voltage stability.

3.2. Scenario 2

In this scenario, the EV parking lot with varying levels of EV penetration is connected to the network during two high-load hours (12 and 13) and two low-load hours (3 and 4). Fig. 5 depicts the network load curve without accounting for the parking of EVs and accounting for EVs with a penetration level of 100 percent EVs.

The strategic deployment of an EV parking lot with varying penetration rates (100%, 70%, and 30%) has been thoroughly

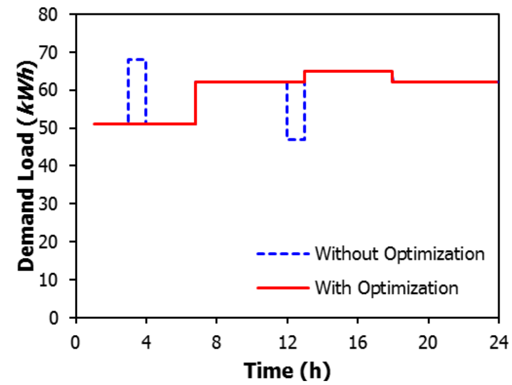

Fig. 3. Network load curve in a high and low demand load hours (scenario 1).

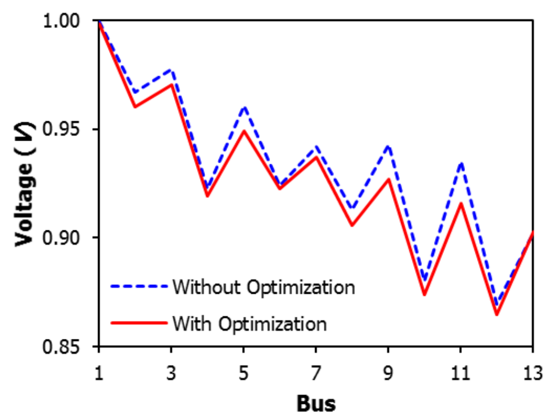

Fig. 4. Network load curve in a high and low demand load hours (scenario 1).

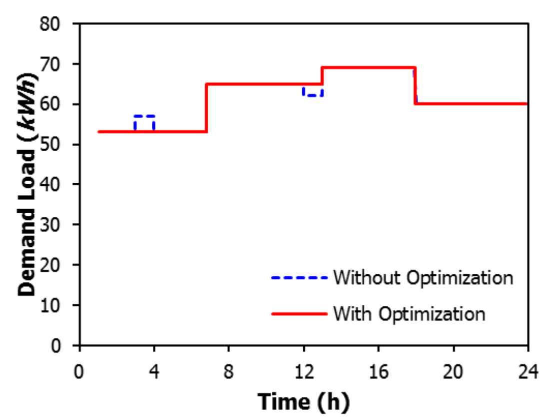

Fig. 5. Network load curve in a high load hour and a low load hour (scenario 2).

investigated. The resulting financial outcomes reveal that the final profit derived from EV parking installations with penetration rates of 100% and 70% amounts to $5,558,100 and $4,232,200, respectively. This represents a reduction in marginal profit compared to the scenario where automobile penetration was at 100%. A comprehensive analysis of the optimization problem under Scenario 2 is presented in Table 3. Notably, at penetration levels of 100% and 70%, the optimal number of EV fleets remains consistent. However, at a 100% EV penetration, the benefits derived from loss reduction, increased reliability, and peak load

Table 3. Scenario 3 comparative results.

Penetration Level	Item	1 buses	2 buses
100%	Number of EVs	18	49
	Minimizing Losses ($)	5,481	9,897
	Peak Load Supply ($)	106,770	247,600
	Overall Profit ($)	112,251	257,497
70%	Number of EVs	18	49
	Minimizing Losses ($)	4,686	8,701
	Peak Load Supply ($)	438,810	937,700
	Overall Profit ($)	44,3496	946,401
30%	Number of EVs	18	48
	Minimizing Losses ($)	1,590	1,959
	Peak Load Supply ($)	97,940	218,100
	Overall Profit ($)	99,530	220,059

provision are more pronounced. Conversely, assuming a 30% EV penetration, the optimal number of EV fleets has increased, but the associated benefits have substantially diminished.

Exploring different usage scenarios, if the EV parking lot is utilized for two hours of high load and two hours of low load, the benefits of reducing losses, enhancing reliability, and providing peak load exhibit a significant increase compared to a scenario with two hours of high load and two hours of low load. This emphasizes the economic advantage for the company in extending the connection of EV parking lots to the network for more hours, without altering the lot's size, especially considering electricity distribution.

Similar to the first scenario, certain buses in the second scenario demonstrate an improved voltage profile during peak load with a 100% EV penetration from the EV parking lot. However, in the second scenario, this improvement is notably more substantial than in the first scenario. As depicted in Fig. 6, the rate of growth in the voltage profile enhancement is significantly amplified, indicating a heightened positive impact on the distribution network's stability and performance.

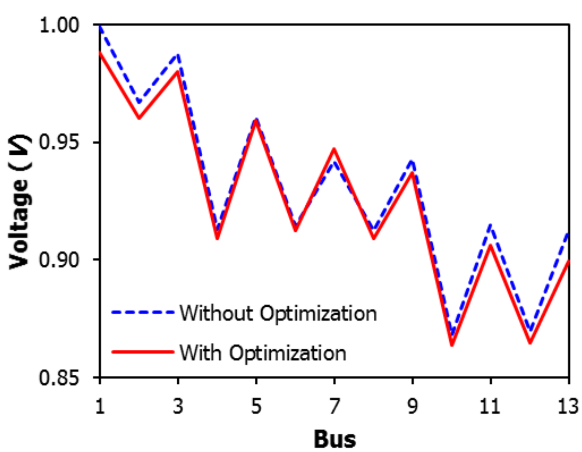

Fig. 6. Voltage variation profile in different buses (scenario 2).

3.3. Scenario 3

The ideal location of electric car parking has been done in this scenario on buses 646 and 611 vs single node 675. During the first six months of the year, EVs parking with penetration levels of 100%, 70%, and 30% are connected to the network in one peak hour (12 p.m.) and one off-peak hour (3 p.m.). Table 3 outlines the results explored on two buses in Scenario 3. According to the findings, increasing the number of parking places for EVs in a network enhances the benefit from minimizing losses, and providing peak load significantly.

4. Conclusion

EVs to the network, and the cost served as a compass for the company in the markets for regulation and ancillary services. In some studies, EVs have been introduced as distributed energy sources in the electric energy market. This has been accomplished by introducing a new actor known as the aggregator, who encourages car owners to connect to the grid while simultaneously maintaining and establishing a relationship between the independent user of the system and the car owners. This is possible because connecting EVs to the grid has very little impact on the power grid.

The current research proposed a multi-objective function for locating the parking spots for EVs within the distribution system in order to meet the demand for electricity during peak hours. When peak demand occurs, an AISA optimization model applied to a fleet of electric vehicles can determine the optimal capacity and location for parking those vehicles. The objective of the optimization that has been suggested is, from the point of view of the company that is responsible for the distribution of electricity, to increase the overall profit. The proposed model is evaluated in this study by using fundamental data as well as prices from the electricity market. According to the findings, the penetration rate of electric vehicle parking installations is quite high. If they are connected to the grid during peak hours, the distribution companies will receive significant benefits, and the voltage profile will be improved. Both of these outcomes are dependent on the availability of the resources. Electrified vehicles' battery capacities, the cost of electricity, the percentage of the total market that is occupied by EVs, and the weighting coefficients that are necessary for optimization will all have an impact on the results. In order to achieve more accurate results, it is necessary to precisely determine both the battery capacity of electric vehicles and the inverter efficiency. According to the findings, increasing the number of parking lots for electric vehicles (EVs) in a network significantly increases the benefit from minimizing losses while also significantly increasing the amount of peak load that can be provided. Therefore, including two parking lots specifically for electric vehicles in a network can bring the total profit up to 129 percent.

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