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A Comparative Study on Charging Time of Electric Vehicles Optimization Using Cuckoo Search and Particle Swarm Optimization Methods

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Abstract— *The implementation of electric vehicles for this specific purpose could potentially cause an impact on the load on the network. From one standpoint, it is more advantageous to initiate the charging process of electric vehicle batteries as soon as they are connected to the grid, in order to guarantee sufficient charge levels in the event of unforeseen events. The current investigation showcases an innovative algorithm specifically engineered for the smart grid, wherein the principal aim is to approximate the time needed to fully charge electric vehicles. The algorithm being evaluated prioritizes the decrease in both the unfulfilled energy demand and the daily load profile standard deviation. The algorithm has been purposefully designed to regulate and supervise the charging process in an efficient manner. The algorithm incorporates various elements pertaining to the anticipated conduct of specific electric vehicles, such as their projected arrival and departure times, as well as their initial charge status upon arrival. In situations involving a substantial quantity of automobiles, statistical techniques are applied to decrease the number of variables, thereby diminishing the algorithm's computational time. The optimization technique implemented in this research is inspired by natural phenomena and is founded upon the cuckoo orphan search pattern. The proposed algorithm and the PSO algorithm were implemented in order to simulate the 34-bus IEEE standard radio distribution network. Upon comparing the outcomes derived from the analysis, it was discovered that the implementation of the CS algorithm led to a substantial decrease in peak load by 33% in comparison to the situation in which no optimization was executed. Furthermore, the CS algorithm accomplished a 27% reduction in peak load, which was superior to the PSO algorithm.*

Keywords—Electric vehicles, optimization, particle swarm optimization, cuckoo search algorithm, load demand.

1. Introduction

As the world continues to grapple with the challenges of climate change and environmental sustainability, electric vehicles (EVs) have emerged as an important part of the solution [1–5]. However, despite their increasing popularity, there are still several obstacles to widespread EV adoption [4–10]. One of the most significant of these is the long charging times associated with EV batteries [11],[12]. The increasing adoption of electric vehicles (EVs) as an eco-friendly transportation solution has raised the need for efficient charging strategies to overcome the limitations of charging infrastructure and optimize the charging time [13]. Reducing the charging time not only improves the convenience for EV owners but also enhances the overall utilization of charging stations and minimizes the strain on the power grid [14]. In recent years, optimization algorithms have emerged as effective tools for addressing complex problems in various domains. Two popular optimization algorithms, Cuckoo Search (CS) and Particle Swarm Optimization (PSO), have shown promising results in solving diverse optimization problems [15]. The optimization algorithms are inspired by natural phenomena and collective behavior, making them suitable candidates for optimizing the charging time of electric vehicles [16],[17]. Finding strategies to optimize EV charging time is crucial to enhancing the usability of these vehicles and contributing to a more sustainable future [18],[19]. This is a complex optimization problem, involving multiple variables and constraints, and traditional optimization methods may not provide efficient or practical solutions.

A fuzzy integer linear programming problem was presented by Hussain et al. [20] to optimize the amount of time spent waiting. They developed a brand new algorithm that is based on a heuristic fuzzy inference system and it reduces the amount of time that electric vehicles (EVs) have to wait at public stations by resolving the objective function. The results of the simulation demonstrate that the proposed FISA demonstrates superior efficiency when compared to other scheduling algorithms that are considered to be state-of-the-art. Yang and Chen [21] presented two global optimization algorithms, one based on the Genetic Algorithm and the other based on Dynamic Programming. Ullah et al. [22] constructed a model for predicting the time required for EV charging. Their goal was to optimize the EV charging schedule

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at DC fast charging stations in order to reduce the cost of charging. One of the global optimization algorithms was based on the Genetic Algorithm, while the other was based on Dynamic Programming. The model was developed with the help of three different machine learning algorithms and used charging event data spanning two years from 500 electric vehicles in Japan. In addition, the parameters of the machine learning algorithms are optimized with the help of the genetic algorithm, the particle swarm optimizer, and the gray wolf optimizer. According to the findings, the optimization models involving the gray wolf performed better than those involving other models.

This study investigates the application of Particle Swarm Optimization (PSO) and Cuckoo Search (CS) techniques to this objective. Both algorithms draw inspiration from nature and have proven to be effective in tackling a wide range of intricate optimization challenges. The PSO algorithm draws inspiration from the social behavior exhibited by fish schooling or bird flocking, whereas the CS algorithm emulates the breeding behavior of cuckoo birds. By applying these two algorithms to the problem of optimizing EV charging times, this study attempts to decrease charging times without compromising battery health or efficiency. A comparative analysis of the performance of the CS and PSO methods is presented, along with an examination of the potential advantages and disadvantages associated with each approach.

The subsequent sections of this paper are structured as follows: Section 2 provides a brief overview of related work in EV charging optimization. Section 3 describes the simulation results and the performance of the algorithms. Finally, Section 4 concludes the paper with a summary of the findings and suggestions for future research directions.

2. MATERIALS AND METHODS

In the comparative study, PSO and CS were chosen for their distinct search and optimization capabilities. PSO exhibits strong exploration capabilities, enabling it to efficiently navigate complex solution spaces, while CS demonstrates excellent exploitation abilities, allowing it to refine solutions to achieve better convergence. This combination of exploration and exploitation in both methods is anticipated to yield a comprehensive analysis of the charging time optimization problem, offering insights into the comparative performance and suitability of these two algorithms in the context of electric vehicle charging time optimization. The utilization of both PSO and CS in this study aims to provide a comprehensive evaluation of different optimization techniques, enabling a deeper understanding of their respective strengths and weaknesses in addressing the charging time optimization challenges for electric vehicles.

2.1. Particle swarm optimization algorithm

PSO is a population-based metaheuristic optimization algorithm inspired by the collective behavior of bird flocks or fish schools. It was first introduced by Kennedy and Eberhart in 1995 and has since gained popularity in solving a wide range of optimization problems.

In PSO, a population of particles moves through a search space to find the optimal solution. Each particle represents a potential solution and has its own position and velocity. The position of a particle represents a candidate solution, while the velocity determines the direction and magnitude of its movement in the search space.

The behavior of particles in PSO is influenced by their own best-known position (pBest) and the global best-known position (gBest) among all particles in the population. Through iterative updates, particles adjust their positions and velocities based on these two factors, aiming to converge towards the global optimum. In search of a space D, the velocity of each particle is determined by a D-dimensional velocity vector named $V_i = (v_{i1}, v_{i2}, ..., v_{iD})$ and the location dimension of each particle is determined by a D-dimensional position vector named $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$ (Eqs. (1) and (2)).

$$\begin{aligned} &v^i[t+1] = wv^i[t] \\ &+c_1 \operatorname{rand}_1 \left(x^{i,pbest}[t] - x^i[t]\right) \\ &+c_2 \operatorname{rand}_2 \left(x^{gbest}[t] - x^i[t]\right), \end{aligned} \tag{1}$$

$$x^i[t+1] = x^i[t] + v^i[t+1]. \tag{2}$$

The update process in PSO involves two main components: cognitive component and social component. The cognitive component enables a particle to remember its best-known position, while the social component allows it to share information with other particles in the population, particularly the global best-known position. By combining these components, particles are able to explore the search space efficiently and exploit promising regions towards finding the optimal solution (Fig. 1).

PSO is characterized by its simplicity, fast convergence, and ability to handle both continuous and discrete optimization problems. It has been successfully applied in various domains, including engineering, finance, image processing, and machine learning. Researchers have also proposed several variants and enhancements to address specific challenges or improve the performance of PSO [23].

PSO offers a powerful optimization technique that can effectively tackle complex optimization problems. Its ability to strike a balance between exploration and exploitation makes it a valuable tool for solving real-world optimization challenges and advancing scientific research.Ultimately, the population advances towards the optimal point using the subsequent relations and with intent. Optimization is decisive because, for values greater than those particles, suitable solutions may be bypassed, and for values less than those particles, suitable search is avoided [24–26].

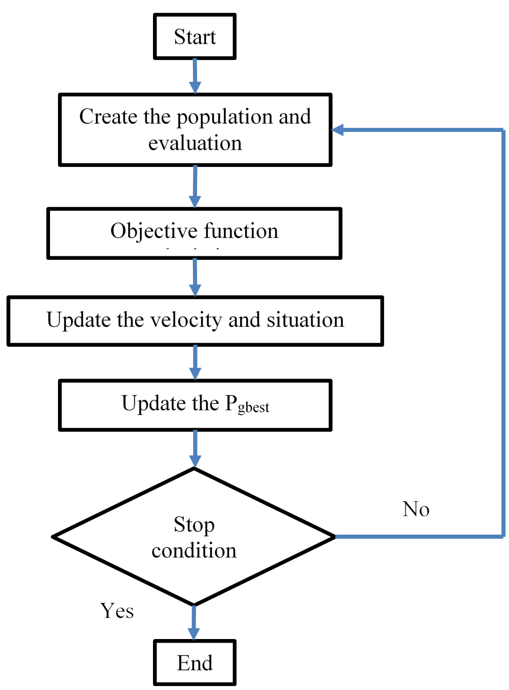

Fig. 1. PSO algorithm flowchart.

2.2. Cuckoo search algorithm

The CS is a nature-inspired optimization algorithm inspired by the behavior of cuckoo birds and their brood parasitism. It was introduced by Xin-She Yang and Suash Deb in 2009 and has since been applied to solve a wide range of optimization problems [27].

In CS, the optimization problem is represented as a nest, and each potential solution is represented as an egg laid by a cuckoo bird. The quality of a solution is determined by its fitness value, with better solutions considered more favorable. The main idea behind CS is the cuckoo's reproductive strategy, which involves laying eggs in the nests of other bird species. Similarly, in the algorithm, cuckoos lay eggs (representing candidate solutions) in randomly selected nests (representing potential solutions). The host nests represent the existing solutions, and eggs determine the new solutions. CS incorporates three main mechanisms: Levy flights, random walk, and competition. Levy flights are random walks that mimic the foraging behavior of cuckoos and allow them to explore the solution space efficiently. Random walk represents the random perturbations applied to the eggs to introduce diversity and prevent premature convergence. Competition occurs between the eggs and the existing solutions, where eggs with higher fitness values replace the corresponding host nests (Fig. 2) [28].

To enhance the performance of CS, researchers have proposed several modifications, such as introducing a local search mechanism, adaptive step size control, and hybridization with other optimization techniques. The CS algorithm has shown promising results in solving various optimization problems, including function optimization, feature selection, image reconstruction, and neural network training. Its ability to handle multimodal and complex problems, along with its simplicity and effectiveness, has made it a popular choice in scientific research and practical applications [29].

The SC algorithm provides a powerful optimization approach inspired by the reproductive behavior of cuckoo birds. By mimicking their strategies, CS offers an efficient and effective method for solving optimization problems, contributing to advancements in various fields of study.

3. RESULTS AND DISCUSSION

The objective function, as described, is specifically formulated for the IEEE 34-bus standard network. It is then implemented using both the CS algorithm and the PSO algorithm. The outcomes obtained from these two algorithms are subsequently compared and analyzed. The network specifications are presented in Table 1.

In order to model the behavior of electric vehicles within the network, we made the assumption that a total of 500 cars were uniformly and randomly dispersed across two parking lots. The spatial distribution of the parking lots within the network is illustrated in Fig. 3.

The battery capacity of each vehicle is stochastically determined from a set of three lithium-ion battery options, namely 10, 16, and 20 kilowatt-hours. The parameters of the distribution function associated with the various variables of the vehicle are chosen from the distribution functions specified in Table 2.

The patterns that are displayed by each electric vehicle were taken into consideration when selecting data points for the time of arrival, the charge level upon arrival, and the time of departure in order to create an environment that is analogous to a typical day. Previous statements indicate that the duration of charging begins subsequent to the moment of arrival, which is made possible by the intelligent network. It is estimated that the charge level will increase by 25% per hour while the device is being charged, and this rate will continue until the device has reached its maximum capacity. It is hypothesized that the daily load of the network, excluding the charging load associated with electric vehicles, should be multiplied to ascertain the load for each individual hour in order to conduct an analysis of the daily load demand. This is done so that the daily load of the network can be determined. The coefficients that are associated with each hour are presented in the figure. In this specific configuration, the period of highest demand occurs between the hours of 12:00 and 15:00, with a subsequent

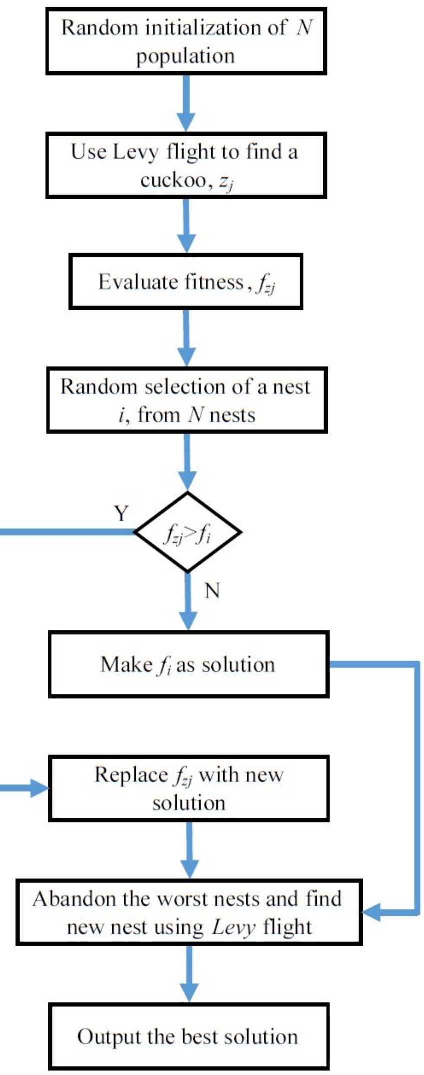

Fig. 2. CS algorithm flowchart.

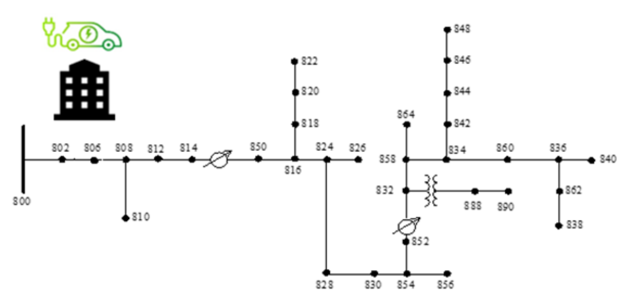

Fig. 3. IEEE 34-bus node test feeder.

decrease in load after 15:00 (Fig. 4). This particular configuration also exhibits a peak demand during the hours of 12:00 and 15:00.

The objective function under consideration is optimized through the utilization of both the PSO algorithm and the CS algorithm. Both algorithms have a repetition count of 200. The PSO algorithm employs an initial population size of 50, while the CS algorithm selects a cuckoo population size of 20.

The PSO algorithm and the CS algorithm both resulted in the greatest number of possible solutions, which are depicted in Fig. 5. The load curve is shown in Fig. 5 in four different scenarios: one without a vehicle, one with optimization, one with optimization of

Table 1. Distributed loads on IEEE 34 node test feeder.

Node A	802	808	818	820	816	824	824	828	854	832	858	858	834	860	836	862	842	844	846
Node B	806	810	820	822	824	826	828	830	856	858	864	834	860	836	840	838	844	846	848
Ph-1 (kW)	-	-	34	135	-	-	-	7	-	7	2	4	16	30	18	-	9	-	-
Ph-1 (kVAr)	-	-	17	70	-	-	-	3	-	3	1	2	8	15	9	-	5	-	-
Ph-2 (kW)	30	16	-	-	5	40	-	-	4	2	-	15	20	10	22	28	-	25	23
Ph-2 (kVAr)	15	8	-	-	2	20	-	-	2	1	-	8	10	6	11	14	-	12	11
Ph-3 (kW)	25	-	-	-	-	-	4	-	-	6	-	13	110	42	-	-	-	20	-
Ph-3 (kVAr)	14	-	-	-	-	-	2	-	-	3	-	7	55	22	-	-	-	11	-

Table 2. Normal distribution of the parameters related to car charging.

Variable	Mean	Standard deviation
Arrival	N(7.5,0.6)	N(0. 3,0.04)
Arrival	charge level	N(0.7,0.1)
N(0.03,0.01)		
Departure	N(18,0.5)	N(1.2,0.06)

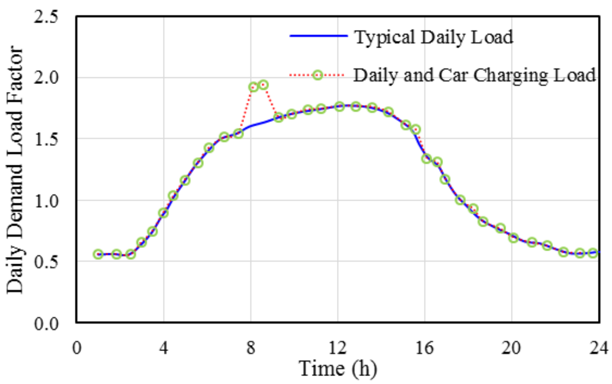

Fig. 4. Typical load and car charging effect on daily load demand.

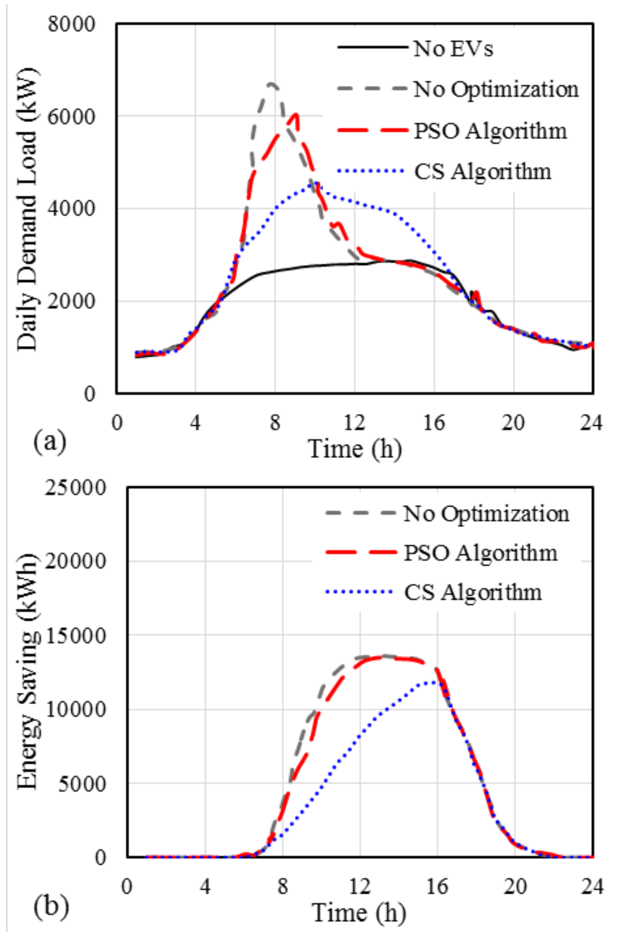

Fig. 5. a) Network load distribution curve b) Energy stored in batteries.

the PSO algorithm, and one with optimization of the CS algorithm. Since the majority of vehicles need to be charged at the same time and are only in the parking lot between 7:00 and 21:00, and since the network experiences its peak load at around 15:00, it is important to take into account the network's peak load in the event that the charging load increases even further. The charging load is almost uniformly distributed and flat during this period, which is one of the advantages of optimizing with the CS algorithm rather than the PSO algorithm. The other advantage is that the CS algorithm optimizes more quickly. Dan has been a witness to the curve in a variety of different ways. It is to be that. This idea is illustrated in Fig. 5 by drawing attention to the number range on the vertical axis, which represents the load. Fig. 5 illustrates that when optimization is performed using the CS algorithm, the peak load is 33% higher than it would be if optimization were not performed, and it is 27% higher than it would be if optimization were performed using the PSO algorithm. As a direct result of this, optimization using the CS algorithm has produced a load curve that is significantly superior to the load curves produced by either not optimizing or using the PSO algorithm. Fig. 5-b also illustrates the three different ways in which the energy that is stored in vehicles that are connected to the network can be viewed. It is clear that the CS algorithm stores significantly less energy than the other two modes of operation. This demonstrates that there is less energy available for self-healing purposes in the event of an 8- to 15-hour power outage in comparison to the peak load curve.

The progression of the values of the objective function variable over the course of the iterations is shown in Fig. 6. As was mentioned earlier, two objective functions are defined: one aims to maximize energy while simultaneously reducing the amount of unsupplied energy, while the other aims to minimize load standard deviation. The overall objective function can be defined as the total weighted standard deviation of the total daily load and the percentage of the total number of cars that are connected to the network at any given time, both of which are then divided by the total amount of energy that is stored in the batteries. Because reducing it maximizes the amount of energy that can be stored, the amount of energy that was used was the opposite of what was intended. In this context, we consider the weight that we've given to each objective function to be equivalent. The value of the overall objective function is shown in Fig. 6-(a), while the energy and standard deviation objective functions for two different algorithms are shown in Figs. 6-(b) and 6-(c), respectively. It is self-evident that the load standard deviation will increase as the energy value increases given the similar behavior that was observed in Figs. 6-(b) and 6-(c). Fig. 6-c demonstrates that there is a trend toward a smaller standard deviation value with both of the algorithms. This suggests that. Because of this, the objective function defined for the standard deviation is given priority over the other objective function. It should come as no surprise that the significance of the two objective functions can vary depending on the network and the specific circumstances. He changed the requirements that they were expected to meet.

Another possible interpretation of this topic is that the energy required to charge the batteries is so great that the rate of degradation of the load curve exceeds the stored energy. Therefore, if we consider a smaller number of cars, we will be close to the state without optimization.

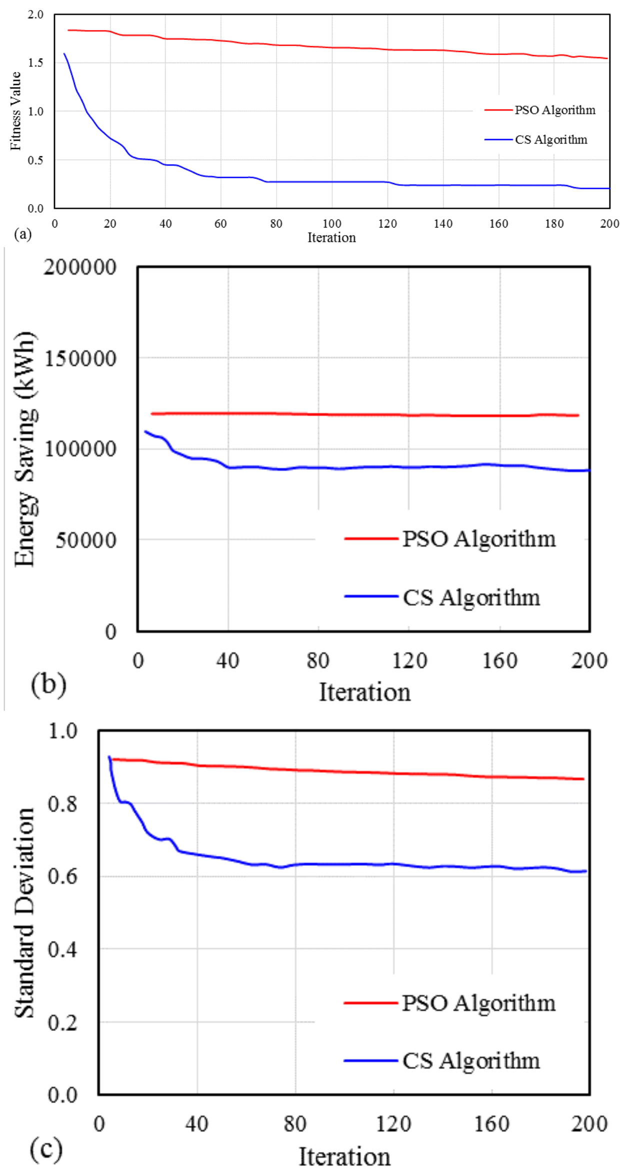

Fig. 6. a) Changes of the overall objective function with two algorithms, b) Changes of the energy objective function with two algorithms, c) Changes of the load standard deviation objective function with two algorithms.

4. Conclusions

This study presents an innovative algorithm for the smart grid that has the purpose of estimating the amount of time that it takes for electric vehicles to charge. The objective of the proposed algorithm is to reduce both the amount of energy that is not supplied and the daily load curve's standard deviation as much as possible. This algorithm is devised to manage and control the charging process in an efficient and effective manner. The algorithm takes into account a variety of factors that relate to the expected behavior of individual electric vehicles. These variables include the estimated arrival time of the vehicles, the time at which they will depart, and the initial charge level that will be present when they arrive. In cases where there are a significant number of automobiles, statistical methods have been used to cut down on the amount of variables, which in turn helps reduce the amount of time needed for the algorithm's computational process. The cuckoo orphan search pattern, which was the basis for the optimization strategy that was used in this investigation, was motivated by observable aspects of the natural world. In order to simulate the IEEE standard radio distribution network, which consists of 34 buses, an implementation of the proposed algorithm as well as the PSO algorithm has been carried out. The results that were obtained have been compared, and the findings indicate that the CS algorithm was successful in reducing the peak load by 33% when compared to the scenario in which optimization was not performed, and by 27% when compared to the PSO algorithm.

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