IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 25 September 2023, accepted 27 October 2023, date of publication 20 November 2023,
date of current version 27 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3334672

RESEARCH ARTICLE

Mitigation of Complexity in Charging Station Allocation for EVs Using Chaotic Harris Hawks Optimization Charge Scheduling Algorithm

V. MANOJ KUMAR[1,2], BHARATIRAJA CHOKKALINGAM[1], (Senior Member, IEEE), AND LUCIAN MIHET-POPA[3], (Senior Member, IEEE)

[1]Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Chennai 603203, India
[2]Department of Mechanical Engineering, SRM Institute of Science and Technology, Chennai 603203, India
[3]Faculty of Information Technology, Engineering and Economics, Østfold University College, 1757 Halden, Norway

Corresponding authors: Bharatiraja Chokkalingam (bharatic@srmist.edu.in) and Lucian Mihet-Popa (lucian.mihet@hiof.no)

This work was supported by the Department of Science and Technology, Government of India, Promotion of University Research and Scientific Excellence (PURSE), under Award SR/PURSE/2021/65.

ABSTRACT The development of EV technology and EV migration is limited by various factors such as sizing of batteries, short driving ranges, optimal operations, and so on. The EV charging faces many difficulties such as waiting time, charging time, uneven charge scheduling, and uneven distributed charging stations. In Charging Station (CS), EVs usually spend much time in queues, mainly during peak hours of charging. Therefore, building a well-established charging station network should be derived from charging demand and proper charge scheduling to assist EVs for getting charged with less cost, less waiting time. Also, it should reduce the number of vehicles scheduling during the peak load time. This work aims to design a scheduling system for EV charging using an optimization strategy of Chaotic Harris Hawks optimization (CHHO) which reduces the total time spent on charging station and the distance of EV origin to destination. CHHO is authenticated using Vehicular Ad-hoc Network (VANET) simulation, and the performances are compared with algorithms Exponential Harris Hawk Optimization, Grey Wolf Optimizer, First in First Out and Random Allocation to demonstrate the efficacy of our technique. The proposed CHHO-based scheduling system yields better performance with the maximum remaining energy and significantly cuts the average travel time, and improves the utilization rate of EVs in charging stations compared to other algorithms. A detailed result and discussions on different case studies by varying number of vehicles and number of charging stations and the corresponding average waiting time were obtained and presented in this paper.

INDEX TERMS Charge scheduling, chaotic Harris Hawk optimization, electric vehicle, electric vehicle scheduling, Harris Hawk optimization, VANET, waiting time.

I. INTRODUCTION

Electric Vehicle technology has been developed in recent years to minimize the emission of Green House Gases (GHG) and to maximize the utilization of renewable energy sources. The replacement of conventional vehicles by adopting EVs with highly supportive renewable techniques in metropolitan cities is a significant way to reduce CO2 emissions [1]. In this 21st century, the utilization of electric vehicles is rapidly increasing as many countries diverted their attention from fossil fuels to energy requirements. There are three main challenges faced by EVs, driving range, long charging time, and high cost [2]. Other obstacles to the migration of EVs are, less charging efficiency, uncertainties in charging location, lack of power, arbitrary procedures, and increases in the grid's maximum demand. In order to resolve this issue, areas with high mobility rates, such as petrol stations, highways, shopping malls, and parking lots, have been supplied with

The associate editor coordinating the review of this manuscript and approving it for publication was Mouloud Denai.

public charging stations in large numbers [3]. Due to the multiple charging stations (CS), various issues may arise related to charging time, cost, scheduling time, distance covered by EVs to reach the destination, improper information management, and so on. To address this issue, a VANET-based scheduling system can be used, to optimize charging time and ensure grid stability [4], as shown in Fig.1.

It collects real-time data on charging demand and available charging infrastructure to allocate the optimal charging schedule for each EV. It dynamically adjusts the charging schedule due to unexpected events, which allows EVs to get prompt charging. This VANET system uses machine learning (ML) algorithms for scheduling charging stations based on various features such as vehicle data, CS data, grid data, and so on. The ML algorithms increase the complexity of the VANET system due to the high-dimension data, [5], [6], which reduces the scheduling performance. Feature Selection (FS) is the required process in the ML methods, and extraction of required features and removal of irrelevant features is the necessary process that has to be done by ML methods. The proper features improve the performance of the ML classifiers. The FS process typically consists of four steps: validity, evaluation, search stop criteria, and feature subset search. The suitable feature detection rate is improved by the TLBO-JAYA algorithm-based intrusion detection technique. This eliminates the irrelevant features and selects the required features [8]. The long-term estimation of the charging station can be analyzed by using this machine learning approach, which estimates the possible rate of increase in the number of vehicles that will be charged in the future. Also, an intelligent transport model and charging management scheme associated with CS have been developed. This method considers the grid availability and on-road traffic scenarios to reduce the impact on the grid as well as vehicle run time [9]. Additionally, the total run time of EVs and its uncertain mobility were been considered for improving the performance of charge management systems. This inclusion reduces the cost of communication between CS to EVs and increases the performance. However, the advantages of this method are been limited due to delay and inefficiency between the Vehicle to Vehicle (V2V) Communications [10]. The communication between the charging station and between EV to EV is been improved by the Hybrid Multi-Population Algorithm (HMPA) based optimization. This helps to optimize Ev's route selection and charge scheduling in the distributed systems. Further, it reduces operational costs by considering factors such as battery charging impact and energy consumption [11]. The significance of this optimization algorithm is further enhanced by incorporating more renewable energy sources into the charging station, which reduces the consumption cost and improves the grid stability [12]. The integration of renewable energy with the charging station improves the grid stability on the peak demand [13]. Smart grids are the developed research area for managing the generating required power during the demand. The concept of a smart grid can be integrated with the charging station to improve the power stability of the charging station, and it avoids the failure of charging stations during grid blackouts. The CS powered with the smart grid requires more data and optimization techniques for efficient operation. The data classification and CS behavior were studied using various heuristic algorithms as in [14]. Later Harris Hawks optimization (HHO) has been incorporated with the grid, smart grid, and renewable energy-based charging stations for improving stability. Different case studies were been carried out to infer the application of the HHO algorithm in the grid-connected charging stations and coordinate the EVs accords to the power availability on CS [15]. Along with that, the converter selection on the battery charging station and vehicle should be optimized for the better efficiency. The butterfly optimization, reinforcement learning, deep learning methods are been used to achieve this [16]. Also, the energy arbitrage and distribution cost is been considered in the evaluation of the developed optimization-based charge scheduling systems. The inclusion of additional parameters improves the charge scheduling process [17]. On the other hand, charge distribution from vehicle to grid (V2G), and various procedures or algorithms used for effective scheduling were been reviewed [18]. A new kind of algorithm called the Proposed Hybrid Optimization Algorithm (PHOA) has been developed, which is a meta-heuristic algorithm based on physics and nature. It is a combination of atom search optimization and tree seed algorithm. It involves the improvement of the charge schedule in the most uncertain environment [19].

Routing of EVs to the charging station involves many problems like routing via shortest path, routing to a fast charging stations and so on. Various optimization techniques were been employed for this problems. The need of smart E-mobility has been discussed and compared with the existing solutions for the deep understanding of the routing concept [20]. An integrated charge scheduling and vehicle coordinating technique is been developed based on exponential Harris Hawks technique [21]. The accuracy of this network may fails on the large scale integrated EV charging stations. In large scale systems, many request may arise simultaneously and the algorithm failed to collect the request and it overwrites the scheduling details will leads to the confusion on the network [22]. VANET strategy is been used for this problem to improve the accuracy on the routing. Ant colony optimization technique is used with the VANET network to classify the requests and decision [23]. A novel intention-aware routing system (IARS) enables vehicles on computing a routing policy. This reduces expected travel time with the considerations of other vehicles and its requests. These considerations affects the estimation of queueing time when other vehicles also selects the same intentions and requests [24]. Deep learning approach [25] and Route search method [26] were been used to address this issues and to improve the routing and scheduling. Apart from the charge scheduling and routing, another method is vehicle to vehicle charging system and

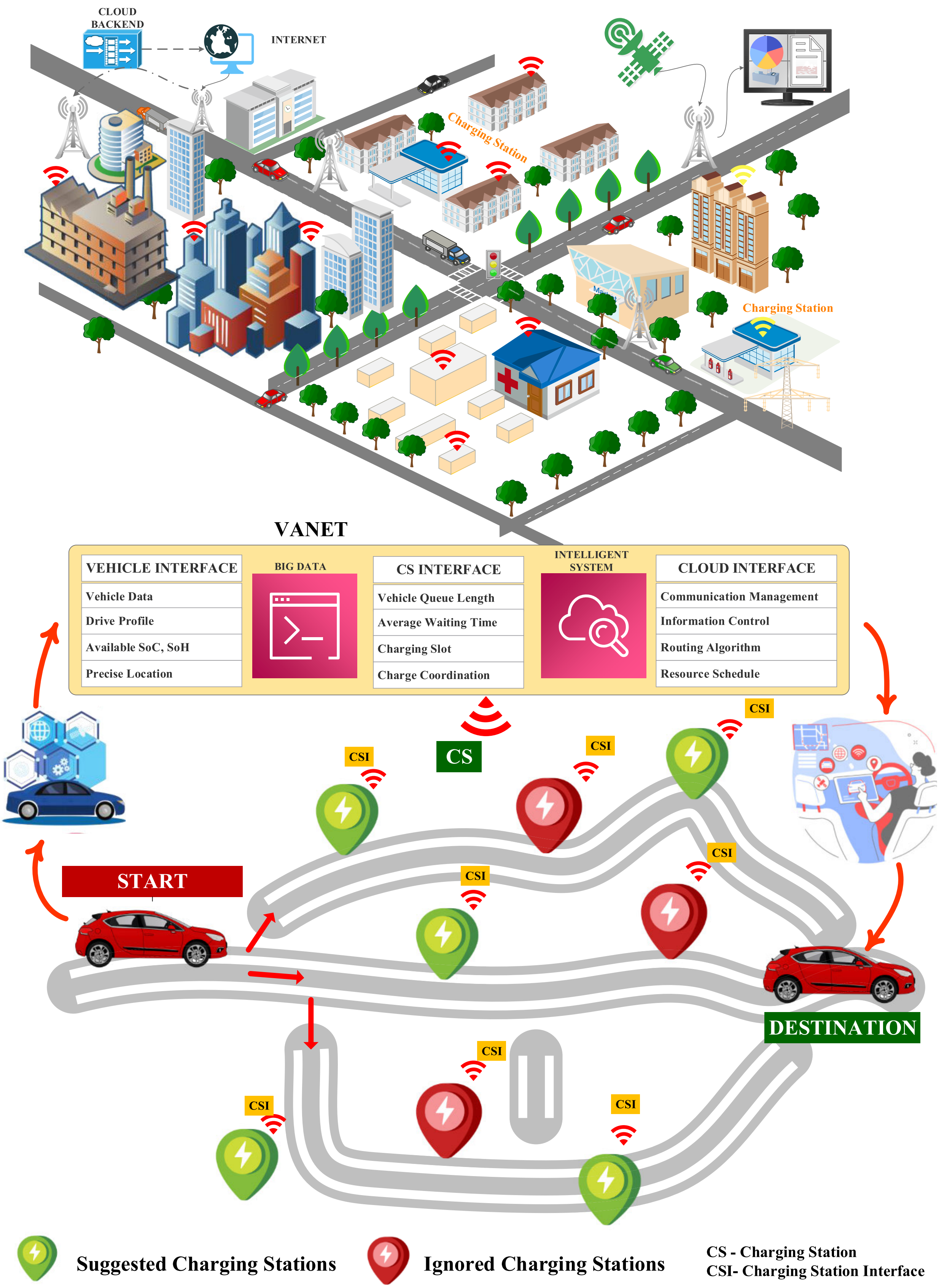

FIGURE 1. Schematic diagram of VANET based routing environment.

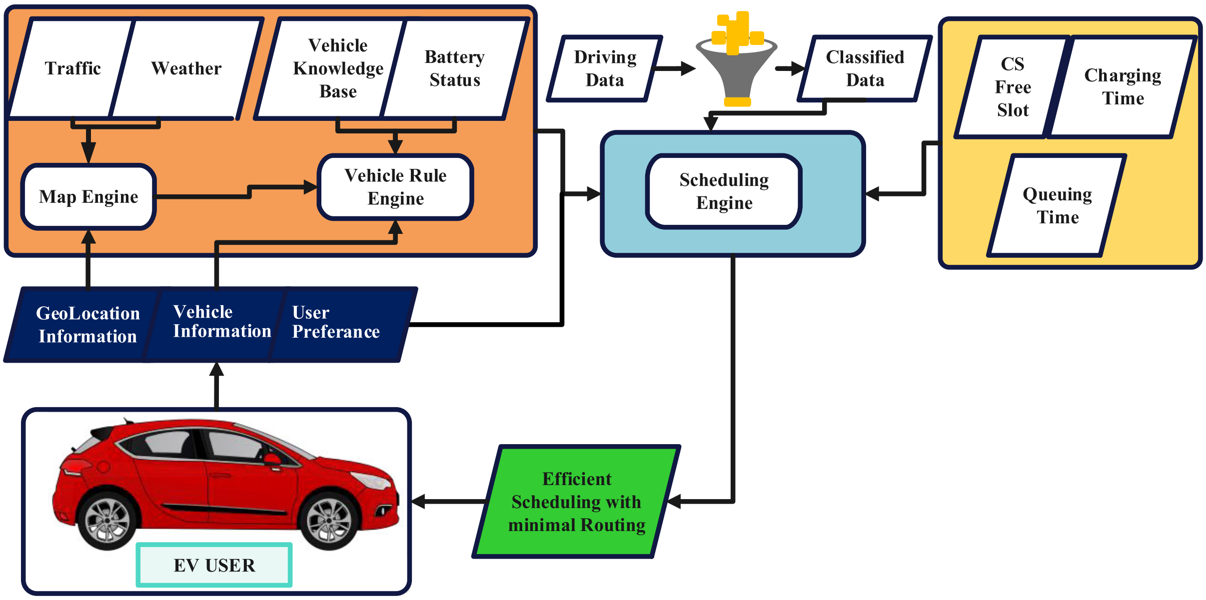

FIGURE 2. Scheduling graph of EV.

its coordination. In the smart city concept the EV charging includes the grid to vehicle (G2V), Vehicle to Grid (V2G) and Vehicle to Vehicle (V2). For this charge scheduling Intelligent Transport System (ITS) framework has been developed in [27] and [28]. Battery characteristics and SoC and SoH measurement are one of the factors to be considered for the charge estimation, travel distance and capable of reaching charging stations [29]. The cost optimization is an essential factor that needs to be considered [30]. The following problem statements were observed form the existing optimization problems, such as less accuracy on charge scheduling, failed to handle more data, scheduling/coordination of vehicle will be overlapped when similar requests are raised, high computation burden on the large scale systems and so on. For addressing these problems in this work a novel combine Harris Hawk and Chaotic Map optimization based VANET system is developed with the improved exploratory behavior of HHO. This method focuses on both charge scheduling and vehicle routing by the consideration of n number of vehicles and n number of charging stations. A detailed analysis is been carried out with the different cases by varying the number of available charging stations and number of vehicles to be charged.

The organization of the proposed work is as follows: Section II describes the architecture of proposed work, Section III describes the combined Harris Hawk and Chaotic Map optimization method, and the proposed system is been validate in different scenario in Section IV, results and discussions is discussed in Section V and the proposed work is been concluded in Section VI.

II. SYSTEM ARCHITECTURE

This section presents the framework for resolving the issue of scheduling EV charging.

A. EVCS-SCHEDULING GRAPH

The EV charge scheduling can be done by collecting the vehicle data and CS data, as shown in figure 2. A global aggregator (GA) is developed to control the charging of electric vehicles (EVs). The EVs communicate their arrival and departure times, as well as the desired charge level, to the GA. A charging schedule is calculated by the GA to minimize costs based on the charging requests and limitations received. Additionally, a routing algorithm is proposed to determine an energy-efficient route with an optimal speed profile for the EVs. The algorithm aims to achieve two objectives: 1) finding the shortest journey time for drivers who prioritize energy efficiency, and 2) generating an energy-efficient route and speed profile for the EVs.

The scenario involves a city with a crowded environment, a network of EVs (X) and charging stations (Y). A sequence of static graphs represents the road network, with EVs and charging stations forming a vehicular network architecture routing scheme. Each graph represents a different scenario, and the shortest delay time (tij) is calculated between an EV (evx) and a charging station (csy). The charging stations have a fixed propagation delay (m) for each charging pile, categorized as slow charging (s) or fast charging (f). The shortest-delay computation is performed by modifying Dijkstra's shortest-path algorithm to account for time-varying links. Each EV has a set of candidate charging stations it can select from, based on the number of edges connected to the charging stations. The edge weights represent the route taken by the EV during the charging process. The number of EVs currently plugged into a charging station indicates its charging capacity. The following definitions outline the charging times for EVs at different charging piles, assuming all charging stations have identical fast and slow charging piles.

B. CHARGING TIME AND CHARGING CAPACITY

The waiting time for the battery to get full charged is one of the major difficulties in EV charging methodology. The battery charging and discharging is lied between the upper bound (E_{higher}) and Lower bound (E_{lower}). When the EV reached the charging station the energy stored in battery is taken as arrival energy ($E_{i,j}$) and it begins to charge. The waiting time is differs with respect to the type of charging. When the vehicle is plugged on slow charging pile, the charging time of the EV can be expressed as equation (1),

$$T^c_{i,j} = \frac{E_{higher} - E_{i,j}}{\Delta e_{slow}} \tag{1}$$

When the vehicle is plugged on fast charging pile, the charging time of the EV can be expressed as equation (2),

$$T^c_{i,j} = \frac{E_{higher} - E_{i,j}}{\Delta e_{fast}} \tag{2}$$

C. MAXIMUM DRIVING DISTANCE

The EV has the limited power to travel, it must be lied on the region to reach the charging station. The vehicle needs to reach the charging station before it reaches the Elower. During the scheduling process, the algorithm takes the available energy on the vehicle as the initial energy (E_i^{int}). The maximum possible distance of the EV can be expressed as equation (3),

$$\varsigma_i = F^{-1}\left(E_i^{int} - E_{lower}\right) \tag{3}$$

D. IMPACT OF DRIVER BEHAVIOUR ON USER'S TRAVEL

The performance of a vehicle control strategy majorly depends on the driving conditions and driving style of the driver, as shown in Table 1. Driving conditions depend on the geographical condition and prevailing traffic along the route. In contrast, driving style correlates to the driver's behavior on how frequently applying acceleration and brakes to the vehicle. The dynamic behavior of the user charging and discharging load profile affects the endurance of the EV, where scheduled trips need to be routed to meet the charging demand of the EV. Proper management of the battery charging and discharging cycle of EV extends the reliability of battery life over a longer period.

On considering the dynamicity of the driving behavior of EVs, The first stage of the driver agent entails to appropriate discharging load profile classified to be as economic drivers (S1), average drivers (S2), and aggressive drivers (S3), the second stage of the agents behave to the charging pattern classified to the coordinated (P1) and uncoordinated charging behavior (P2) and the final stage of the driver agent based on the socio-economic thinking categorized as Time oriented (E1) and cost-oriented behavior model (E2). Based on these data, the charging station will provides the recommendations to the uses. The deciding factor is been considered as 0 when the user neglect the recommendation and it will be 1 when user accept the recommendations.

TABLE 1. Driver behavior encoding.

Users	Ti min	Driving Style			Charging pattern		Socio-Economic Thinking		Deciding Factor
		S1	S2	S3	P1	P2	E1	E2	C
User A	T1	1	0	0	0	1	0	1	0
User B	T1	0	1	0	0	1	1	0	0
User C	T1	0	0	1	1	0	0	1	0
User A	T2	1	0	0	0	1	1	0	1
User B	T2	0	0	1	0	1	1	0	1
User C	T2	0	0	1	1	0	0	1	0

E. BATTERY DEPTH OF DISCHARGE

According to Newton's Second Law, the convenient power corresponding to the net force exerted on the vehicle determines how much a vehicle's speed (v), changes over time (t), or its acceleration (dv/dt) with mass (m). The speed differential can be measured using equation 4.

$$F_t - F_r = \frac{dv}{dt}(m + \xi) \tag{4}$$

where F_t is the tractive force, F_r is the resistive forces against motion, and ξ is the rotational inertia. A vehicle accelerating at a certain rate requires a certain tractive force to overcome driving resistances which can be calculated using equation (5),

$$F_t = F_r + (m + \xi).a \tag{5}$$

The total force that is opposes the motion can be written as in the equation 6, where, a, A, v, g, r, are the air mass density, aerodynamic resistance coefficient, projected area on the plane perpendicular to the direction of the vehicle's movement, relative speed to the wind, gravitational acceleration, and coefficient of rolling resistance, respectively.

$$F_r = \frac{1}{2}.\rho.F.\mu_a.A.v + m.g.(\mu_r + \sin\alpha) \tag{6}$$

The instantaneous tractive power P_t can be calculated by the equation (7),

$$P_t = v.F_t \tag{7}$$

When the speed of an object is increased from v_i to v_j in the period t_j to t_i, the energy consumption associated with the motion on a particular edge (i, j), $E^e_{i,j}$, can be calculated using equation 8.

$$E^e_{i,j} = \int_{t_i}^{t_j} P_{tr}.dt \tag{8}$$

The energy used on an edge (i, j) can be described as a function of the kinetic and potential energy changes and the losses (Eloss) due to the rolling and air resistance can be obtained using equation (9),

$$E^{e}_{i,j} = \Delta p^{i,j} + \Delta p^{i,j} + \Delta El^{i,j}_{loss} \tag{9}$$

Also, it is considered is to attain the details of EVs that it requires energy to recover or to drive. When $E^{e}_{i,j} > 0$, it is possible to calculate the propulsion energy needed, $E^{pro}_{i,j}$ conversely, when $E^{e}_{i,j} < 0$, it is possible to calculate the regenerative energy $E^{regi}_{i,j}$.

$$E^{pro}_{i,j} = E^{e}_{i,j}.\eta_e^{-1} \tag{10}$$

$$E^{regi}_{i,j} = E^{e}_{i,j}.\eta_{regi} \tag{11}$$

Assuming that rolling and air resistance are the key factors to be fixed along the edges of the road graph affecting energy consumption. Different driving style speed profiles are selected and provided as input to the system. The system utilizes these speed profiles to estimate the depth of discharge of the battery, which helps in determining the amount of electricity discharged by the battery. This estimation is crucial for calculating the state of charge (SoC) of the electric vehicle (EV) and enables effective management of the charging process at the charging station. The model enables estimation of the amount of battery power consumed by an EV during travel to a charging station, considering the distance travelled. This information is crucial for determining the remaining battery power when the EV arrives at a charging station. This leads to improved management of charging infrastructure and resources, allowing for better optimization of EV charging schedules.

F. ELECTRIC VEHICLES TRAVEL TIME

The trip time of multiple EVs to the same charging station varies since they are spaced at varying distances from it. This results in various CS queue patterns. For scheduling an electric vehicle EV_x to a charging station (n_j), its trip time ($\boldsymbol{T^T_{i,j}}$) can be stated as follows in equation (12),

$$T^{T}_{i,j} = \frac{d_{i,j}}{v_i} \tag{12}$$

where v_i denotes the speed of an EV and $d_{i,j}$ the distance between an EV and a CS(n_j), respectively.

G. ELECTRIC VEHICLES QUEUING TIME

The queuing time for EVs at a charging station depends on the charging completion time of the EVs ahead of them. Factors such as the number of fast and slow charging stations in use, the availability of remaining charging piles, and the sequence of EVs arriving at the charging station influence the queuing time. The time it takes for an EV to reach a chosen location at the charging station is referred to as the arrival time. The arrival time represents the travel time from the EV's current position to the selected charging station location. Both the queuing time and the arrival time play a crucial role in determining the overall charging process and efficiency at the charging station.

Assume that charging station n_j has μ^f_j and μ^s_j fast charging and slow charging piles. Let $\Omega^f_j (N^f_j = |\Omega^f_j|)$ and $\Omega^S_j (N^S_j = |\Omega^S_j|)$ symbolize the ordered queue of EVs at charging station n_j that select the fast and slow charging piles for charging. The EVs' arrival time determines the queue's f_j and s_j placement. The queueing time for the EV at the station can be calculated as equation (13)

$$T^{Q}_{i,j} = \beta^{f}_{i,j} - T^{T}_{i,j} - T^{C}_{i,j} \tag{13}$$

If $u^f_j + 1\hat{} \leq mi^f_j$:

$$\beta^{f}_{i,j} = T^{T}_{i,j} - T^{C}_{i,j} \tag{14}$$

If $1\hat{}=1$ and $u^f_j + 1\hat{} > mi^f_j$:

$$\beta^{f}_{i,j} = \max(\min(\tau_j), T^{T}_{i,j}) - T^{C}_{i,j} \tag{15}$$

If $1\hat{}>1$ and $u^f_j + 1\hat{} > mi^f_j$:

$$\beta^{f}_{i,j} = \max(\min(\tau_j \cup (\beta^{f}_{1,j}, \beta^{f}_{2,j}, \ldots, \beta^{f}_{i-1,j})), T^{T}_{i,j}) - T^{C}_{i,j} \tag{16}$$

where function $min\left(\tau_j\right)$ selects the 1^{th} smallest element from set f_j, and f_j represents the set of EVs completion charging times that pick the fast pile charging at charging station n_j.

III. PROPOSED CHARGE SCHEDULING OPTIMIZATION

A population-based metaheuristic optimization algorithm called Harris Hawks optimization (HHO) was developed to mimic Harris hawks' cooperative behaviour and hunting tactics. HHO is hybridized with ten distinct chaotic maps to alter its key parameters in this work.

A. PROPOSED CHAOTIC HHO

The proposed chaotic HHO algorithm combines the Estimate Weighted Moving Average (EWMA) and HHO algorithms to perform EV charging scheduling. It leverages the advantages of both methods to improve solution quality. The HHO algorithm promotes inquiring behavior and smoothly transitions between exploitation and exploration using sinusoidal and tree maps. The solutions' quality improves with an increasing number of iterations. The HHO algorithm is effective in handling complex search spaces and provides satisfactory local optimum results. The EWMA algorithm introduces modest changes in processing target values, addressing certain problems encountered in the HHO algorithm. The proposed algorithm uses a fitness function that considers various factors such as distance, average waiting time, energy, and the number of EVs requiring charging. The fitness function is designed to balance visual quality and forensic detectability. The algorithm follows a solution encoding approach, involves fitness evaluation, and utilizes the proposed exponential HHO method. Fig. 3 illustrates the flowchart of the exponential HHO algorithm, showcasing an ideal solution.

When an electric vehicle (EV) is started, its parameters such as energy level and potential driving distance are calculated and updated. If the EV has sufficient energy to

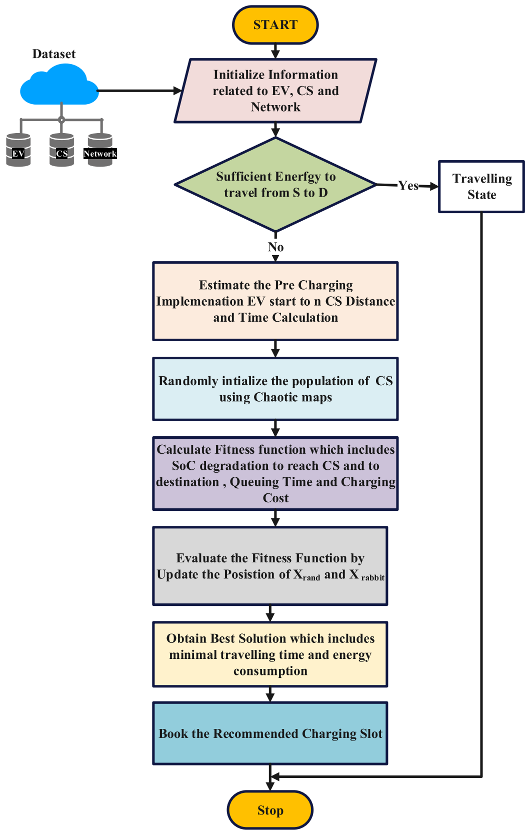

FIGURE 3. Flow chart CHHO alterations.

reach its destination, it will immediately begin driving. If the energy level is insufficient, the EV needs to perform charging scheduling and charge planning. Once the EVs are charged, they can resume driving mode. A Global Aggregator (GA) acts as a bridge between the EVs and a cloud server (db), providing an interface for communication and data exchange. The cloud server database facilitates data storage and retrieval for the EVs. In this system, EVs are considered nodes within the Vehicular Ad-hoc Network (VANET), enabling communication and coordination among vehicles and roadside infrastructure.

1) SOLUTION CODIFICATION

This section discusses the encoding of solutions for electric vehicle scheduling using the proposed chaotic HHO method. The encoding process involves two main steps: charging schedule encoding and decision variable encoding. For charging schedule encoding, a binary string is used to represent the charging schedule for each electric vehicle. The binary string's length is determined by the number of electric vehicles and time intervals. Each bit in the binary string corresponds to a specific time interval, indicating whether the vehicle is scheduled for charging during that interval. Decision variable encoding involves representing the decision variables of the chaotic HHO algorithm in binary form. The binary string's length is determined by the number of decision variables, with each bit representing a specific decision variable. To obtain the complete binary string representing the solution, the binary strings for the charging schedules and decision variables are concatenated. Also, a minimal waiting period constraint is applied to ensure contiguous charging schedules for each electric vehicle. A sliding window approach is used to detect and invalidate any gaps in the charging schedule. If a gap is found, the corresponding bit in the binary string is set to 0. By following this encoding scheme and incorporating the minimal waiting period constraint, the proposed chaotic HHO method can generate effective solutions for electric vehicle scheduling.

2) FITNESS

The proposed algorithm includes a fitness function and equations to calculate distance, average waiting time, energy, and the number of EVs requesting charging. The fitness function combines these variables using equal weight factors of 1/4 for each. The fitness function as shown in equation (19), is given by:

$$Fitness = \frac{1}{4}\left(k + l + (1 - m) + n\right) \tag{17}$$

where k is the distance of each EV to the charging station, calculated as in equation 18, m represents the energy required for charging each EV, and it is assumed to be constant, n represents the number of EVs that raised a request for charging.

$$K = \frac{1}{\alpha \times P} \sum_{i=1, i \neq 0}^{P} s(a_i^d - a_m) \tag{18}$$

L represents the average waiting time for each EV, calculated using Equation 19 and 20.

$$L = \frac{1}{\alpha \times P} \sum_{i=1, i \neq 0}^{P} sL_i^d \tag{19}$$

$$L_i^d = (L_D^E - S_d) \tag{20}$$

where L_d^i represents the waiting time of the i^{th} EV at d^{th} iteration and R_d^e indicates the predicted end time of charging the i_{th} EV, and S_d signifies the arrival Time of ith EV at CS.

B. CHHO ALGORITHM STEPS

The Chaotic HHO algorithm is utilized to search for optimal charging schedules. It generates new candidate solutions using existing charging schedules and search operators like crossover, mutation, and selection. Chaotic maps or operators are employed to introduce diversity and enhance the exploration-exploitation balance. The steps of the proposed CHHO algorithm are as follows:

1) PROPOSED CHHO ALGORITHM

Proposed Algorithm shows the procedure of the CHHO optimization algorithm to find the best possible solution for scheduling the electric vehicle.

Step 1: *Initialization: Generate an initial population of charging schedules randomly within the problem's constraints.*

$$C = \{C_1, C_2, C_3, C_4, C_{5......}, C_{i......}, C_j\} \tag{21}$$

where C_i represents the i_{th} solution and j is the complete number of solutions.

Step 2: *Chaotic Map: Apply a chaotic map to each charging schedule to enhance the diversity of solutions and improve the exploration-exploitation balance.*

Step 3: *Step 3: Selection: Select the best charging schedules in the population based on their fitness.*

Step 4: *Step 4: Harris Hawk Behaviour: Update the position of the selected charging schedules using the Harris hawk behavior, which includes exploration and exploitation strategies.*

$$C(d+1) = \Delta C(d) - T\dot{:}HC_{rab}(d) - C(d) \tag{22}$$

where h stands for the random strength of the rabbit, crab(d) refers to the location of the rabbit at iteration d, t stands for the energy of the escaping prey, and $\delta c(d)$ shows the difference between the position vector of the rabbit and current Location during iteration d.

Step 5: *Crossover and Mutation: Apply crossover and mutation operators to the selected charging schedules to generate new candidate charging schedules and evaluate the fitness of this new schedule*

Step 6: *Elitism: Select the best charging schedules from the new population and the previous population to form the next generation of charging schedules.*

Step 7: *Termination: Repeat steps 2 to 6 until a stopping criterion is met, such as reaching a maximum number of iterations or a threshold for the fitness value.*

IV. DATA COLLECTIONS

A. DATASET ENVIRONMENT

For the validation of the proposed algorithm, a real-time EV charging and scheduling environment is considered as shown in Fig.4. The map shows the details of charging station and routes in the Chennai city India which is one of the major metropolitan cities in Asian continent. The various routes available to reach the destination F from the starting point A and the number of available charging station in midway were considered. The algorithm possesses all these data and creates the possible charging option for the EV. Also, these data are fed to the SUMO simulation interface visualization, which can display the movement of all the cars with the street layouts, traffic conditions and speed limits during the simulation process. This algorithms also takes the consideration of Advanced Urban and Rural Transportation System (AURTS) and Advanced Vehicle Control System (AVCS).

Algorithm Finding out the optimal parameter for scheduling the electric vehicle

Input:
N: population size
T: maximum number of iterations.
n: Number of Groups
Output:
The rabbit's fitness value and habitat.
Using combination of five different chaotic maps to create the initial population's point:
By means of chaotic variables yik ∈ [0, 1], where k = 1, 2, 3..., N. M denotes the initial population.
To obtain the starting population of the related solution space, we used inverse mapping.
Start
While stopping condition is not meet do Increase layer l++
Step 1: Determine the Hawks' fitness values;
Make Xrabbit the best location for rabbits.
Update the value of E for each Xi using Equation (3), and the vector Xi is updated using Equations (2) and (18)
if |E| > 1; Generate randomly the parameters: r1, r2;
$b = e^{((5x)pi.*(2-t/t_max))}$
if q < 0.6 then
Vector $Y_i$is Updated
If q ≥ 0.6 then

$$Xi(t+1) = Xrandom(t) * \omega(t) - |Xrandom(t) * b - 2 \times r2 \times Xi(t)|$$

end
end
end
Step 2: Select the nth groups
if |E| < 1 then
if r ≥ 0.6 and |E| ≥ 0.6 then
Update the vector Xi using Equation (7);
end
else if r < 0.5 and E | ≥ 0.5
Update the vector Xi using Equations (8)–(11);
end
else if r < 0.5and |E| < 0.5
Update the vector Xi using Equations (12) and (13);
end
end
end
Step 3: Find the optimal neighborhood CS
Optimal neighborhood disturbance
Find the X(t) and X∗(t)
End
Return x
Return Rabbit
Step 4: Majority vote the ln-1 layers node's parameter and send to MC for adjustment
End

TABLE 2. Charging station parameters.

CS Id.	Latitude and Longitude	Charging Type	No. of Fast piles	No. of Slow piles
1	12.746520029416594, 80.00482977008141	Type 2 (25Kw)	4	3
2	12.717930375790978, 79.9903189797837	Type 2 (25Kw)	3	0
3	12.767450475203367, 80.00714224672414	Type 2 (25Kw)	4	2
4	12.850362709472613, 80.14158361670088	Type 2 (25Kw)	6	4

TABLE 3. Electric vehicle realistic features.

Parameters considered	Tata Nexon	Hyundai Kona	MG ZS
Kerb Wt.(kg)	1400	1535	1518
Extra Payload(Kg)	75	75	75
Drag Coefficient	0.18	0.29	0.28
Vehicle Length(cm)	3993	4180	4314
Vehicle Width(cm)	1881	1800	1809
Vehicle Height(cm)	1606	1570	1620
Frontal Height(sq.m)	2.47	2.4	2.53
Transmission Efficiency (%)	85	85	85
Overall Gear Ratio(: 1)	9.1	7.98	7.5
Rolling Resistance(Ω)	0.02	0.02	0.02
Tire Diameter(mm)	664.4	668.3	668.3
Battery (kWh)	30.2	39.2	44.5
Battery Voltage(V)	320	327	394
Claimed Range(Km)	312	452	340
Tire Size	215/60	215/55	215/55
Motor Type	PMSM	PMSM	PMSM
Max Power(ps)	129	136	142.7
Peak Motor Power(kW)	94.8	100	104.9
Max Motor Torque(Nm)	245	395	350

B. EV CHARGING PILES DATA

The algorithm takes the CS ID, CS location and number of charging piles (including fast and slow) for the recommendation of the best routes and charge scheduling. The required details collected from the CS shown in Fig.4. Specifications are given in Table 2.

C. REALISTIC EV FEATURE

The realistic features of EVs are differed with respect to the brands, motor specifications, and technology. So, it is required to feed the data of different EVs to the algorithm for the efficient recommendations. In this analysis, three different EVs from different manufactures were considered and the corresponding details are given in table 3. Based on these data EV model is built in MATLAB/Simulink® to validate the behaviour of each EVs with different drive profile like aggressive, moderate, and conservative.

TABLE 4. Trip distance estimation.

Trip Id	Start (S)	Destination (D)	d (km)	t (min)
1	13.031602972147216, 80.24329502896585	12.746520029416594, 80.00482977008141	44	67
2	13.0419045296694, 80.0466239110148	12.717930375790978, 79.9903189797837	49.3	73
3	12.812196884868987, 80.07435009009615	12.96146202248871, 80.18421337054708	28.3	47
4	12.828265560486875, 80.0427643969665	13.059138788598371, 80.21167919065981	38.7	49

D. DATA GENERATION AND PRE-PROCESSING

Based on the road network, available EV charging stations (specification of CS), and the EV specifications, the algorithm builds the required data set to validate the fitness function. The preprocessing of the data set includes the following details.

1) DATA GENERATION

Random GPS coordinates for EVs were created in Chennai city (Figure 5). These GPS coordinates are adjusted with the appropriate road network segments to simulate the position of moving EVs. The GPS coordinates of each electric vehicle are mapped to the nearest equivalent road network segments in this stage using a global map matching method. Also, it plots the possible destination of each EV based on the Point of Interest (POI).

2) DATA CLEANING

This step uses a heuristic-based outlier identification approach to clean the unprocessed CS location data. Convert the CS GPS coordinates to the OSM road network's coordinate system.

3) TRIP DISTANCE ASSESSMENT

The OSM road network calculates the shortest navigational distance between EVs and charging stations using the Dijkstra algorithm. The distance and time calculation for the EVs to reach CS from various starting points using the algorithm is given in the table 4.

4) ENERGY CONSUMPTION AND CHARGING TIME CALCULATION

The total energy required for the EV is been calculated by considering the SoC at the time of request and the required to reach the charging station. Equations (1) and (2) are used to measure the required energy needed to charge the EV up to 100% SoC. Also it obtains the path for EVs to reach the CS with minimum travel time. The sample calculation is given in table 5. This continuous monitoring stores the user priority related to optimum charging.

5) QUEUING TIME EVALUATION

The proposed algorithm measures the queueing time for the EVs at each charge stations. This requires the vehicle

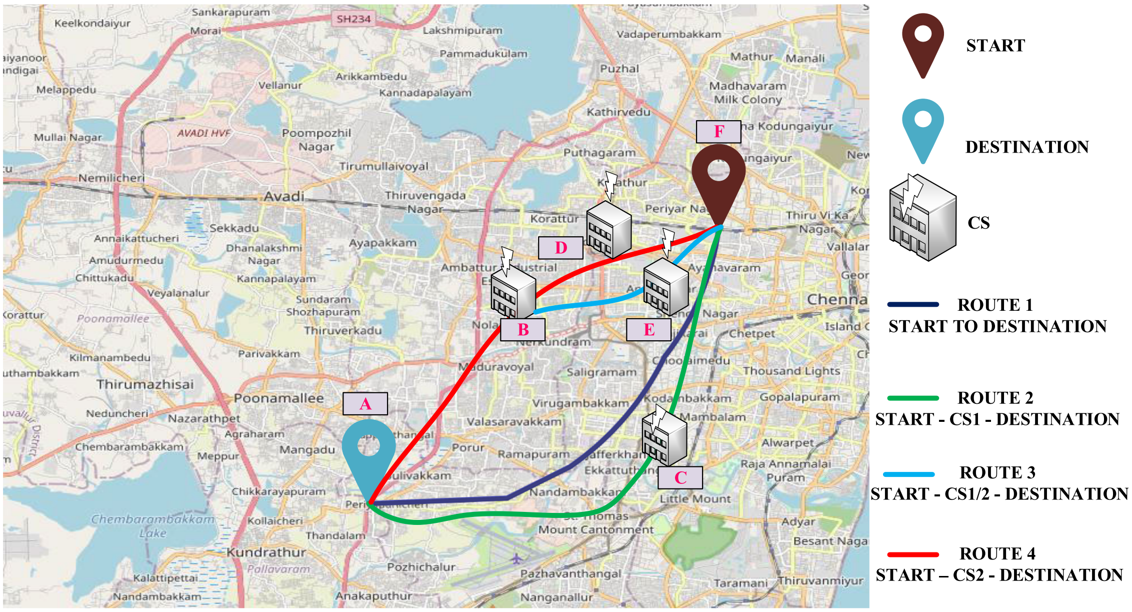

FIGURE 4. Road map environment using OSM.

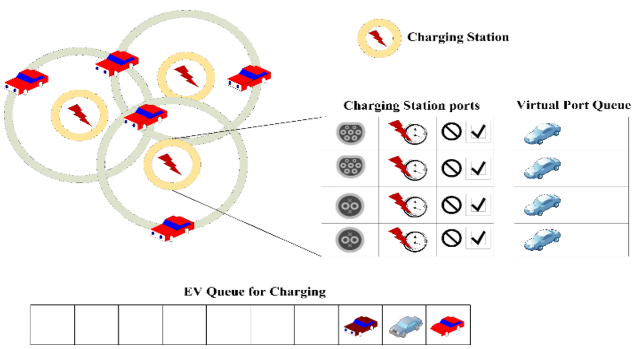

FIGURE 5. Queuing of EV in CS.

occupied on CS, details of available fast/slow piles, requests raised for the charging, number of preference on the each CS and so on as shown in Fig.6. The simulation model used to determine the position of each EV in the queue is shown in Fig. 7. The test results are collected from 200 EVs and 20 EV charging stations in Chennai with the assumption that the average speed is v=60km/h and the battery capacity is 1000Ah.

V. RESULTS AND DISCUSSION

The performance proposed CHHO algorithm has been validated using different possible cases between two points A, B with six charging stations located in between at different distances. The total distance between points A and B are 50 km. The real time data has been collected from the local place as shown in figure 7. Two points A, B were fixed where a point is the institution and B point is the Chennai. The total distance between these two points is 50 km. The

TABLE 5. Time and energy efficient route comparison.

Route Number	Segment Code	Minimum energy		Minimum Travel Time	
		Energy	Time(s)	Energy	Time(s)
1	OE	163	79	123	79
2	EF	100	97	269	97
3	FD	296	60	263	60
4	CI	211	111	216	111
5	ID	204	78	234	78
6	OA	119	134	138	134
7	OB	231	26	291	26
8	OC	243	128	153	128
9	AB	208	102	93	102
10	BH	292	97	79	97
11	HD	297	39	99	39
12	OG	291	88	297	88
13	GD	80	30	199	30
14	GI	179	98	276	98
15	IH	209	101	267	101

charging station location were given in table 6. There are different possibilities of scenarios like vehicle starting point, available SoC, maximum distance the vehicle can travel with available SoC, most nearest and longest charging station the vehicle can reach and so on. When the number of vehicles are increased, the behaviour and complexity of the charge scheduling algorithm will be increased. The efficient algorithm should be capable to handle the complexity, computation burden and charge allocation with minimum waiting time. With this different behaviours the proposed CHHO algorithm has been validated in different possibilities of eight cases using ten vehicles with different drive cycle, different types of vehicles, same starting point, same destination,

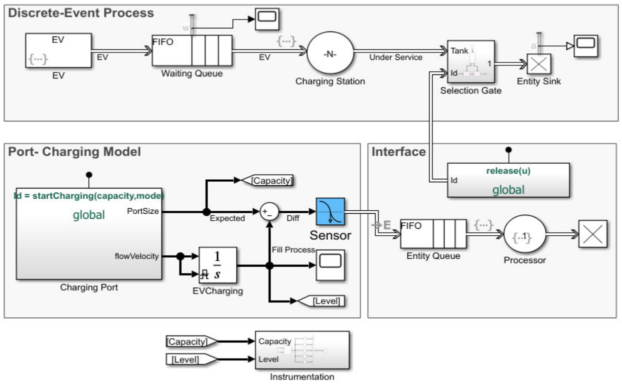

FIGURE 6. Simulink model for queue time estimation.

TABLE 6. Details of charging stations.

Charging Stations	From A	From B
CS1	5	45
CS2	30	20
CS3	40	10
CS4	20	30
CS5	15	35
CS6	25	25

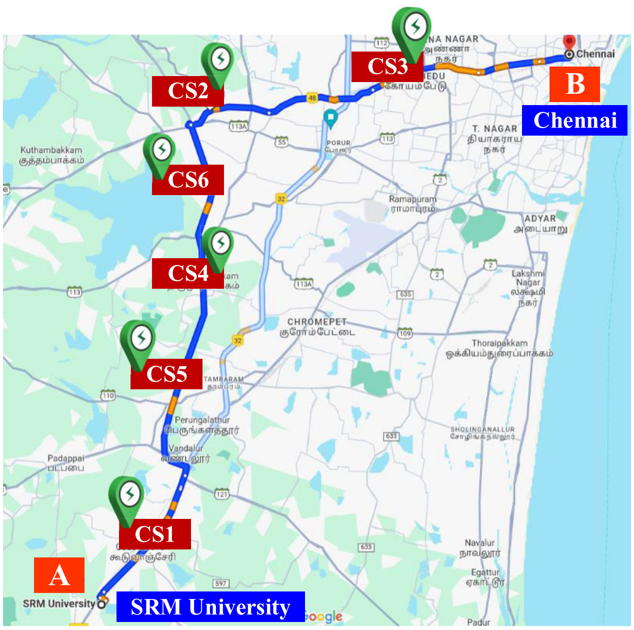

FIGURE 7. Available charging stations between A and B.

different starting point, different destination, same SoC, different SoC and so on. Also the performance of the proposed algorithm has been compared with the HHO, FCFS and random allocation algorithm.

A. CASE 1: DIFFERENT STARTING POINT, DIFFERENT SoC

In this case, five vehicles are assumed to start it journey from point A to destination B. Similarly five vehicles are started from point B to point A. All the ten vehicles had different SoC. When the charging request has raised from each vehicle, the proposed algorithm collects the following data from the vehicle such as starting point, current location, destination, SoC, energy drained per 1%SoC, maximum distance it can travelled and so on. Based on this it allocate the charging station. For an example, when a vehicle has more SoC and it can travel maximum distance as compared to other vehicles, then the algorithm allocates the charging slot for the vehicle at the longest distance with less charging time. In this case there are five vehicles are started from point A and five vehicle are started from B. In this case, the charging algorithm separates the vehicle as two category based on SoC. The vehicle with less SoC will be allotted to the nearby charging station, and vehicles with higher SoC will be allotted to distant charging stations. This allows the system to reduce the waiting time of the vehicle. The vehicle scheduled at the nearest charging station will be the charging station scheduled for the vehicle with high SoC from the other point. The vehicle from the distant point needs to spend more time for travel whereas, this time reduces the waiting time at the charging stations. In this case, the average waiting time of the proposed CHHO algorithm is 0.4 mins whereas HHO algorithm has 5.75 mins, random scheduling has 8.85 mins and FIFS algorithm has 8.08 mins as the average waiting time. The charging station allotment, waiting time and total travel time of each vehicle are given in table 7.

B. CASE 2: SAME STARTING POINT (A), DIFFERENT SoC

Case 2 discusses the behavior of proposed CHHO algorithm to schedule the vehicles from same starting point to same destination with different SoC. In this case the some of the vehicles are having higher SoC and some of the vehicles are having lower SoC. There are six charging stations are available in between the starting point and destinations. The vehicle with higher SoC can access maximum charging stations in the path whereas the vehicle with low SoC can access limited charging station as it can travel with the available SoC. The algorithm took all these things information, and schedule the vehicle with higher SoC to the maximum distant charging station it can travel and schedules the nearest charging station to the vehicles with lower SoC. Whereas in FCFS, random scheduling algorithm, allocates the higher SoC vehicle to the nearby charging station that makes the distant charging station as idle and increases the waiting time, total travel time. In this case the proposed CHHO algorithm has the average waiting time of 6.03mins and the HHO, FCFS, random method had 8.40mins, 13mins and 17.30mins. The charging station allotment, waiting time and total travel time of each vehicle is given in table.

C. CASE 3: SAME STARTING POINT (B): DIFFERENT SoC

This case is more similar to the case 2, where the starting point is considered B instead of A. The distance between the charging stations are differed as compared to the case 2. The charging station 1 is located far away from the starting

TABLE 7. Charge allocation of vehicle and average charging time in case 1.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	FCFS	Random	HHO	CHHO	HHO	CHHO	FCFS	Random	HHO	CHHO
1	A	B	51	1	1	5	3	0	0	0	0	63.5	63.5	66	71.25
2	A	B	32	5	5	1	1	0	0	0	0	70.75	70.75	68.25	68.25
3	A	B	40	4	6	2	4	0	0	0	0	70	71.25	72.5	70
4	A	B	47	1	3	4	2	13.5	0	0	1	78	73.25	68.25	71.75
5	A	B	39	5	6	3	5	20.75	21.25	0	0	89.75	92.75	75.25	69
6	B	A	64	3	1	3	1	0	0	55.25	0	61.5	70.25	116.75	68.25
7	B	A	25	6	3	6	3	0	3.5	0	0	75	74.75	75	71.25
8	B	A	33	4	6	5	2	10	42.5	0	0	84.25	115.5	75.5	71.75
9	B	A	62	3	5	2	4	11.5	3	2.25	3	73.5	71.25	66.75	70
10	B	A	44	6	5	4	5	25	18.25	0	0	95.25	91	71.5	68.25

TABLE 8. Charge allocation of vehicle and average charging time in case 2.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	HHO	CHHO	FCFS	Random	HHO	CHHO	FCFS	Random	HHO	CHHO
1	A	B	51	1	1	5	4	0.00	0.00	20.75	0.00	63.50	63.5	86.75	67.25
2	A	B	32	2	5	5	4	0.00	0.00	0.00	17.25	74.50	70.75	70.75	89.25
3	A	B	40	3	5	2	3	0.00	20.75	0.00	0.00	75.00	89.5	72.5	75
4	A	B	47	4	3	1	6	0.00	0.00	20.00	0.00	68.25	73.25	84.5	69.5
5	A	B	39	5	1	6	1	0.00	13.50	0.00	10.25	69.00	80	71.5	76.75
6	A	B	64	2	1	6	1	48.75	30.00	21.50	0.00	115.25	90.25	86.75	60.25
7	A	B	25	1	4	1	6	13.50	0.00	0.00	19.50	83.50	73.75	70	94.5
8	A	B	33	2	4	4	5	24.50	23.75	0.00	13.25	98.75	95.5	71.75	83.75
9	A	B	62	3	4	4	5	25.00	45.50	21.75	0.00	94.50	110	86.25	63.25
10	A	B	44	4	5	3	2	18.25	39.50	0.00	0.00	87.25	107.25	74	71.5

TABLE 9. Charge allocation of vehicle and average charging time in case 3.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	FCFS	Random	HHO	CHHO	HHO	CHHO	FCFS	Random	HHO	CHHO
1	B	A	51	5	6	6	0.00	0.00	0.00	0.00	73.50	71	68.5	68.5	1
2	B	A	32	4	4	2	0.00	45.00	24.50	14.50	72.00	119.5	99	86.5	2
3	B	A	40	6	2	5	0.00	0.00	0.00	0.00	67.50	71.25	70	73.75	3
4	B	A	47	4	3	1	0.00	0.00	12.00	0.00	70.75	70.75	77.75	74.5	4
5	B	A	39	3	5	4	0.00	0.00	0.00	0.00	74.00	67.75	74	72.75	5
6	B	A	64	1	1	3	0.00	28.25	1.00	0.00	65.25	98.5	71.25	61.5	6
7	B	A	25	6	6	3	17.50	21.25	18.50	11.50	88.75	96.25	93.5	82.75	3
8	B	A	33	4	4	6	22.00	20.75	0.00	18.50	93.75	95	74.25	91.5	2
9	B	A	62	5	3	2	38.75	16.00	0.00	0.00	100.75	84.25	62	64.5	3
10	B	A	44	3	2	4	20.75	17.75	20.00	0.00	92.25	84.25	89	71.5	4

TABLE 10. Charge allocation of vehicle and average charging time in case 4.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	FCFS	Random	HHO	CHHO	HHO	CHHO	FCFS	Random	HHO	CHHO
1	A	B	30	1	1	2	1	0.00	0.00	50.00	0.00	68.75	68.75	125	68.75
2	A	B	30	1	6	1	2	18.75	23.75	0.00	25.00	87.5	97.5	68.75	100
3	A	B	30	1	2	4	4	37.50	25.00	22.50	22.50	106.25	100	95	95
4	A	B	30	5	6	2	5	38.25	47.50	25.00	0.00	109.5	121.25	100	71.25
5	A	B	30	5	5	6	6	17.00	0.00	0.00	0.00	88.25	71.25	73.75	73.75
6	A	B	30	5	1	2	1	0.00	37.50	0.00	18.75	71.25	106.25	75	87.5
7	A	B	30	4	6	1	2	0.00	0.00	18.75	0.00	72.5	73.75	87.5	75
8	A	B	30	1	2	4	4	56.25	0.00	0.00	0.00	125	75	72.5	72.5
9	A	B	30	4	2	5	5	22.50	50.00	0.00	21.25	95	125	71.25	92.5
10	A	B	30	2	1	6	6	0.00	18.75	23.75	23.75	75	87.5	97.5	97.5

point B. This limits the number of accessible charging station for the charge scheduling, which reflects on the waiting time on nearby charging stations. The proposed CHHO algorithm offers the minimum average waiting time as compared to

TABLE 11. Charge allocation of vehicle and average charging time in case 5.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	FCFS	Random	HHO	CHHO	HHO	CHHO	FCFS	Random	HHO	CHHO
1	B	A	30	2	3	6	3	0.00	0.00	23.75	0.00	72.50	70	97.5	70
2	B	A	30	3	3	2	2	0.00	20.00	0.00	0.00	70.00	90	72.5	72.5
3	B	A	30	6	2	3	6	23.75	0.00	0.00	0.00	97.50	72.5	70	73.75
4	B	A	30	2	3	3	3	22.50	40.00	20.00	20.00	95.00	110	90	90
5	B	A	30	3	2	2	2	20.00	22.50	22.50	22.50	90.00	95	95	95
6	B	A	30	1	1	1	1	0.00	0.00	18.75	18.75	68.75	68.75	87.5	87.5
7	B	A	30	2	4	4	5	45.00	0.00	0.00	0.00	120.00	72.5	72.5	71.25
8	B	A	30	4	5	6	4	0.00	0.00	0.00	0.00	72.50	71.25	73.75	72.5
9	B	A	30	1	2	5	1	18.75	60.00	21.25	0.00	87.50	135	92.5	68.75
10	B	A	30	6	5	1	5	0.00	21.25	0.00	21.25	73.75	92.5	68.75	92.5

TABLE 12. Charge allocation of vehicle and average charging time in case 6.

V.No	S.P	Des	Ini. SoC	Charging Station Allotted				Waiting Time				Total Travel Time			
				FCFS	Random	HHO	CHHO	FCFS	Random	HHO	CHHO	FCFS	Random	HHO	CHHO
1	A	B	45	1	1	1	1	0.00	0.00	0.00	0.00	65	65	65	65
2	A	B	45	2	1	5	1	0.00	15.00	0.00	15.00	71.25	80	67.5	80
3	A	B	45	3	2	4	5	0.00	0.00	0.00	0.00	73.75	71.25	68.75	67.5
4	A	B	45	4	1	6	5	21.25	30.00	0.00	17.50	90	95	70	85
5	A	B	45	5	1	4	6	22.50	70.00	18.75	0.00	90	135	87.5	70
6	A	B	45	2	5	3	3	21.25	0.00	0.00	0.00	90	72.5	66.25	66.25
7	A	B	45	3	2	2	3	23.75	0.00	0.00	16.25	90	68.75	68.75	82.5
8	A	B	45	4	5	4	2	0.00	22.50	40.00	0.00	71.25	95	111.25	68.75
9	A	B	45	5	1	3	4	0.00	45.00	20.00	0.00	72.5	120	86.25	71.25
10	A	B	45	6	3	6	2	0.00	0.00	20.00	18.75	70	66.25	90	87.5

the other methods and the corresponding charging times are 4.45mins for CHHO, 7.60mins for HHO, 9.90mins for FCFS and 14.90mins for the random charge allocation. The allocation of charging station, waiting time and total travel time of each vehicle is given in table.

D. CASE 4. SAME STARTING POINT (A), SAME SoC

In this case, all vehicles depart from point A with a similar SoC of 30%. With this available SoC, the vehicle can be scheduled for charging at the stations with in the distance the vehicle can travel with 30% of SoC. The charging stations CS1 is placed at 5km, CS2 is placed at 30 km, CS3 is placed at 40km, CS4 is placed at 20km, CS5 is placed at 15 km and CS6 is placed at 25 km away from point A. CS1, CS4, CS5 and CS6 charging station can be accessible by all the vehicles whereas, when the vehicle accessed by the by the WLTC and FTP75 drive cycle, vehicle can reach the CS6 as per the considerations discussed in section IV. The proposed CHHO algorithm offers the minimum average waiting time as compared to the other methods and the corresponding charging times are 11.13mins for CHHO, 14mins for HHO, 19.03mins for FCFS and 20.25mins for the random charge allocation. The allocation of charging station, waiting time and total travel time of each vehicle is given in table.

E. CASE 5 DIFFERENT STARTING POINT, SAME SoC (MINIMUM)

In this case, five vehicles are assumed to start it journey from point A to destination B. Similarly five vehicles are started from point B to point A. All vehicle are having same SoC and these vehicle had the limits the available charging stations for the scheduling. The charging stations CS1, CS2, CS4, CS5, CS6 are accessible from the starting point of A, and the charging stations CS2, CS3, CS4, CS6 are accessible from the starting point of B. Here, the charging stations CS2 and CS6 can be accessible by the vehicle starting from both the points of A and B. In this case, the common accessible charging stations need to be carefully scheduled to avoid the high waiting time. The proposed algorithm efficiently handles this problem and allocates 1 vehicle from starting point A, and 1 vehicle from starting point B, whereas the other algorithm schedules 2 from one point and 1 from another point which increases the waiting time of third allotted vehicle. In this case, the average waiting time of the proposed CHHO algorithm is 8.25mins whereas HHO algorithm has 10.63mins, random scheduling has 13.00mins and FIFS algorithm has 16.36mins as the average waiting time. The charging station allotment, waiting time and total travel time of each vehicle is given in table 13.

F. CASE 6 DIFFERENT STARTING POINT, SAME SoC (MODERATE)

This case similar to the case 5, but the vehicle had moderate amount of SoC of 45%. All the vehicles starts from point A and point B can able to access all charging stations in the network. This allows the system to choose the optimum charging station with less repeated scheduling for reducing the waiting time. The proposed CHHO algorithm efficiently

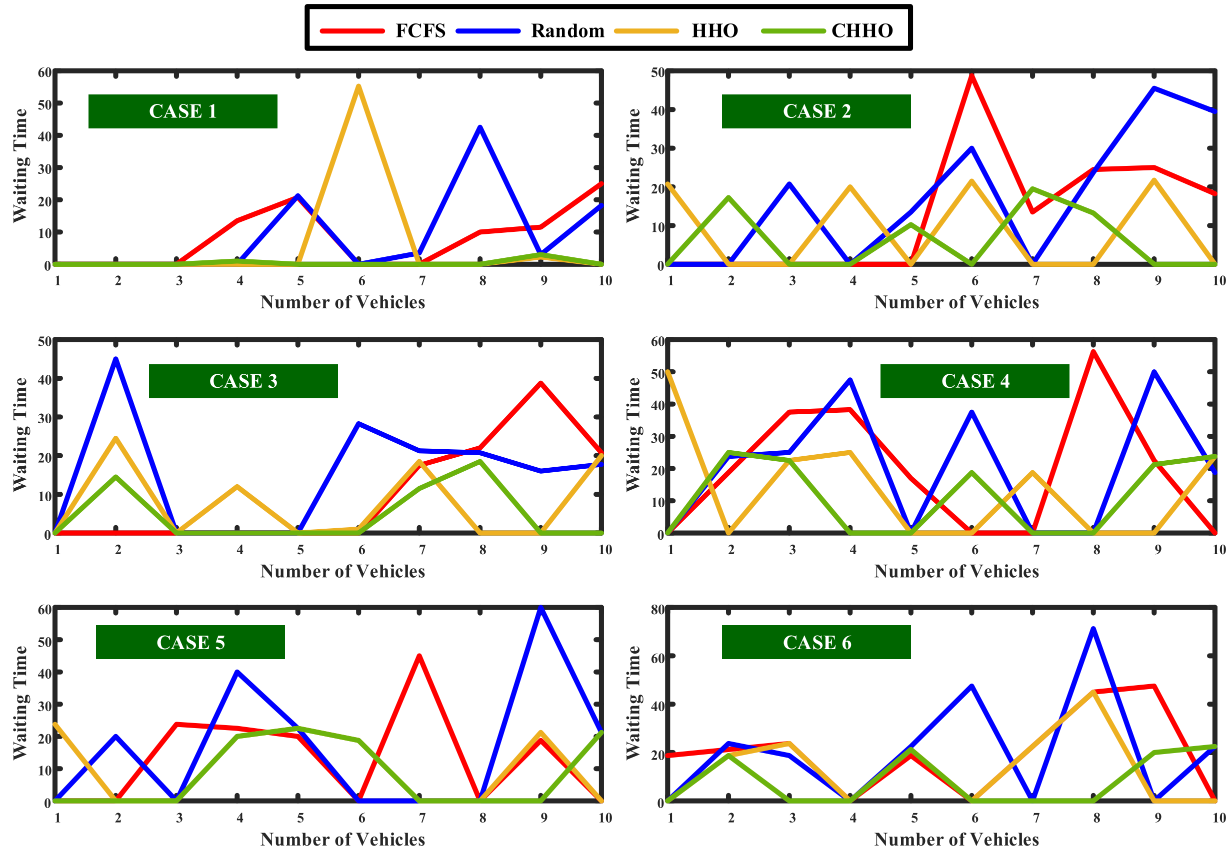

FIGURE 8. Waiting time of each vehicles in different charging scheduling algorithms.

handles this scenario and allocates the charging stations with the average waiting time of 6.75mins, which is the best among other methods. The corresponding allotted charging station, waiting time and total travel time is given in table. The waiting time of each vehicle in all the 6 cases are plotted as in figure 9 for the showing the efficient operation of proposed CHHO algorithm. In each cases the waiting time in CHHO algorithm is more optimized due to the distributed charge scheduling. The average waiting time of each cases are calculated and plotted as a comparative bar chart as given in figure 11. The HHO algorithm based charge scheduling has good performance as compared to the other two methods. The proposed modification in HHO algorithm outperforms the HHO and efficiently handles the charge scheduling problem.

Apart from this 10 vehicle, 6 charging stations, the efficiency of the proposed CHHO algorithm needs to be evaluated in the real time environment. For that different possibilities from the environment is considered like different number of electric vehicles and different number of charging stations. In case 1, 50 vehicles are considered and its average waiting time with respect to the number of charging stations such as, 50 vehicles allotted to 10 charging stations, 50vehicsl allotted to 20 charging stations, 50 vehicles allotted to 30 charging stations, and 50 vehicles allotted to 40 charging stations. In each cases all vehicle can able to access all charging stations with the available SoC in battery. Similarly, the number of vehicles has been varied like 100, 150, and 200 to evaluate the performance with the available charging stations. Figure 11 shows the average waiting time over the 100 iterations when the 50vehicles are allotted to the different number of charging stations. Each conditions has

TABLE 13. Average waiting time on different scenarios.

S.No	No of Vehicles	No of CS	Average Waiting Time (mins)			
			Random	FCFS	HHO	CHHO
1	50	10	70.34	71.12	51.47	44.95
		20	52.71	50.69	37.55	32.87
		30	32.73	31.58	23.89	20.47
		40	16.53	16.40	12.55	10.1
2	100	10	114.41	118.94	89.09	76.34
		20	91.99	85.35	67.55	59.09
		30	62.30	60.97	44.38	39.64
		40	29.66	29.09	22.07	18.48
3	150	10	77.78	73.54	58.01	50.75
		20	59.29	60.18	44.82	39.29
		30	49.41	46.85	35.11	30.44
		40	38.14	35.66	28.29	24.16
4	200	10	194.63	184.25	133.16	121.04
		20	129.50	125.46	99.16	87.93
		30	100.82	94.65	69.61	62.34
		40	50.87	48.83	35.51	31.47

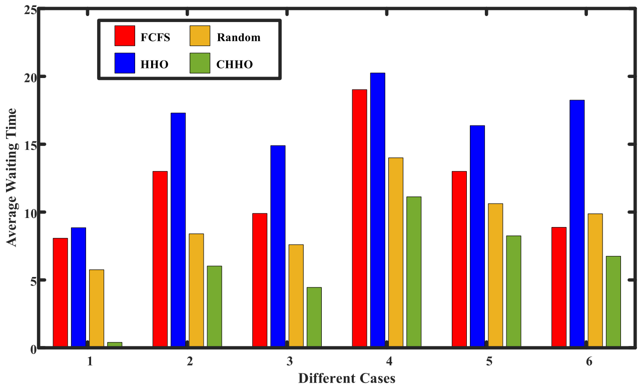

FIGURE 9. Average waiting time of charging scheduling algorithms.

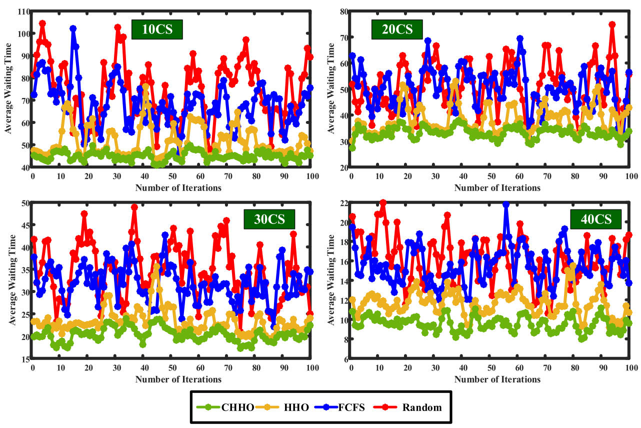

FIGURE 10. Average waiting time of 50vehicles in different number of charging stations.

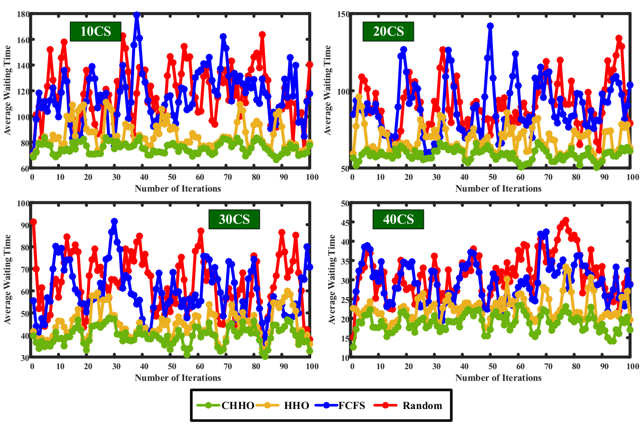

FIGURE 11. Average waiting time of 100vehicles in different number of charging stations.

been simulated for 100 iterations and average waiting time on 100 iterations are given in table 13.

The proposed CHHO algorithm outperforms all other charge scheduling algorithms in all cases. The various average waiting time of CHHO is when 50 vehicles are scheduled in at 10 charging stations 44.95mins average waiting time, when scheduled at 20 charging station it gives 32.84mins,

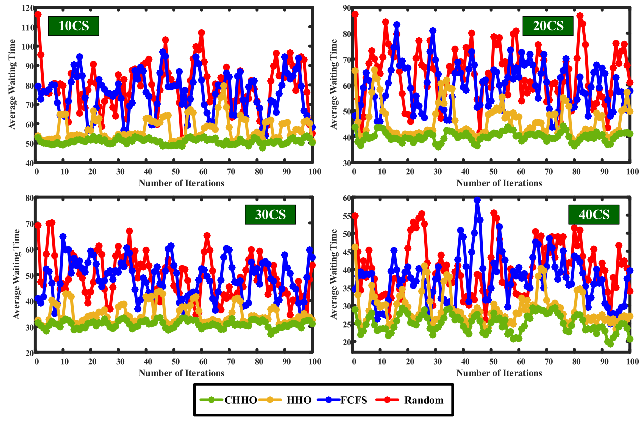

FIGURE 12. Average waiting time of 150vehicles in different number of charging stations.

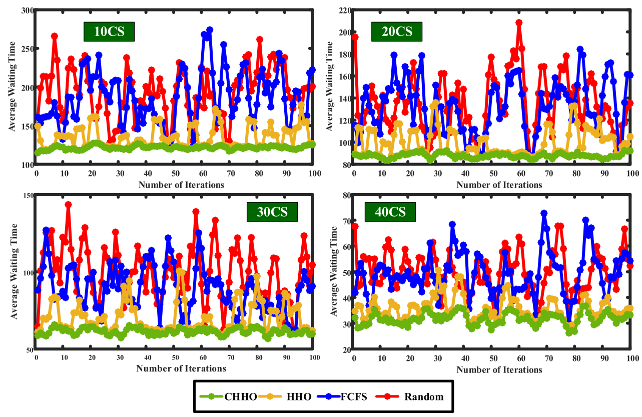

FIGURE 13. Average waiting time of 200vehicles in different number of charging stations.

when scheduled at 30 charging stations it gives 20.47mins and when scheduled at 40 charging stations it gives 10.1mins. Similarly the corresponding average charging stations on different number of vehicles and charging stations are given in table. The charging time for each case on each iteration are plotted as graphs using Python and MATLAB software. Figure 10 shows the average waiting time of 50 vehicles that are allotted to different number of charging stations in 100 iterations. Figure 11 shows the average waiting time of 100 vehicles allotted to different number of charging stations in 100 iterations. Figure 12 shows the average waiting time of 150 vehicles allotted to different number of charging stations in 100 iterations. Figure 13 shows the average waiting time of 200 vehicles which are allotted to different number of charging stations in 100 iterations.

VI. CONCLUSION

The proposed CHHO charge scheduling algorithm has been proposed and validated in different scenarios to acquire the performance. The attained results were compared with the existing algorithms, such as HHO, FCFS. Generally, EV charging is recognized as a time-consuming process, a factor that often prompts individuals to prefer conventional vehicles for their convenience. Nevertheless, the introduction of the CHHO algorithm has demonstrated some potential in addressing the challenges associated with electric vehicle charging scheduling, consequently reducing waiting periods. By framing this issue as a multi-objective optimization problem and incorporating a newly developed fitness function, the CHHO algorithm is capable of determining the optimal charging schedule efficiently. This approach not only minimizes the average waiting time but also takes into consideration factors such as distance, energy consumption, and the number of EVs in circulation. This proposed method holds a significant advantage over traditional approaches, demonstrating the capability to effectively manage the charging demands of numerous EVs. Notably, it reduces the overall waiting time by 12% compared to the HHO algorithm, thus promoting the efficient utilization of resources. Additionally, the CHHO algorithm outperforms other optimization techniques by adeptly avoiding local optima and converging towards the global optimum. In conclusion, the CHHO algorithm emerges as a promising solution for scheduling electric vehicle charging. The performance can be further enhanced by considering the real time data such as real-time traffic and charging station status data which has been the future scope of this work.

REFERENCES

[1] L. Canals Casals, E. Martinez-Laserna, B. A. García, and N. Nieto, "Sustainability analysis of the electric vehicle use in Europe for CO_2 emissions reduction," *J. Cleaner Prod.*, vol. 127, pp. 425–437, Jul. 2016, doi: 10.1016/j.jclepro.2016.03.120.

[2] P. B. Bautista, L. L. Cárdenas, L. U. Aguiar, and M. A. Igartua, "A traffic-aware electric vehicle charging management system for smart cities," *Veh. Commun.*, vol. 20, Dec. 2019, Art. no. 100188, doi: 10.1016/j.vehcom.2019.100188.

[3] Y. Luo, G. Feng, S. Wan, S. Zhang, V. Li, and W. Kong, "Charging scheduling strategy for different electric vehicles with optimization for convenience of drivers, performance of transport system and distribution network," *Energy*, vol. 194, Mar. 2020, Art. no. 116807, doi: 10.1016/j.energy.2019.116807.

[4] S.-N. Yang, W.-S. Cheng, Y.-C. Hsu, C.-H. Gan, and Y.-B. Lin, "Charge scheduling of electric vehicles in highways," *Math. Comput. Model.*, vol. 57, nos. 11–12, pp. 2873–2882, Jun. 2013, doi: 10.1016/j.mcm.2011.11.054.

[5] Y. Cao, O. Kaiwartya, R. Wang, T. Jiang, Y. Cao, N. Aslam, and G. Sexton, "Toward efficient, scalable, and coordinated on-the-move EV charging management," *IEEE Wireless Commun.*, vol. 24, no. 2, pp. 66–73, Apr. 2017, doi: 10.1109/MWC.2017.1600254WC.

[6] A. S. Al-Ogaili, T. J. Tengku Hashim, N. A. Rahmat, A. K. Ramasamy, M. B. Marsadek, M. Faisal, and M. A. Hannan, "Review on scheduling, clustering, and forecasting strategies for controlling electric vehicle charging: Challenges and recommendations," *IEEE Access*, vol. 7, pp. 128353–128371, 2019, doi: 10.1109/ACCESS.2019.2939595.

[7] J. Barco, A. Guerra, L. Muñoz, and N. Quijano, "Optimal routing and scheduling of charge for electric vehicles: A case study," *Math. Problems Eng.*, vol. 2017, pp. 1–16, 2017, doi: 10.1155/2017/8509783.

[8] M. Aljanabi, M. A. Ismail, and V. Mezhuyev, "Improved TLBO-JAYA algorithm for subset feature selection and parameter optimisation in intrusion detection system," *Complexity*, vol. 2020, pp. 1–18, May 2020, doi: 10.1155/2020/5287684.

[9] F. Xie, C. Liu, S. Li, Z. Lin, and Y. Huang, "Long-term strategic planning of inter-city fast charging infrastructure for battery electric vehicles," *Transp. Res. E, Logistics Transp. Rev.*, vol. 109, pp. 261–276, Jan. 2018, doi: 10.1016/j.tre.2017.11.014.

[10] Y. Cao, T. Wang, O. Kaiwartya, G. Min, N. Ahmad, and A. H. Abdullah, "An EV charging management system concerning drivers' trip duration and mobility uncertainty," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 4, pp. 596–607, Apr. 2018, doi: 10.1109/TSMC.2016.2613600.

[11] S. Barshandeh, F. Piri, and S. R. Sangani, "HMPA: An innovative hybrid multi-population algorithm based on artificial ecosystem-based and Harris hawks optimization algorithms for engineering problems," *Eng. Comput.*, vol. 38, no. 2, pp. 1581–1625, Apr. 2022, doi: 10.1007/s00366-020-01120-w.

[12] W. Dong, Z. Wang, and W. Guo, "Optimal charging schedules for electric vehicles with renewable energy sources," *Energy*, vol. 116, pp. 493–503, Sep. 2016.

[13] S. Alwar, D. Samithas, M. S. Boominathan, P. K. Balachandran, and L. Mihet-Popa, "Performance analysis of thermal image processing-based photovoltaic fault detection and PV array reconfiguration—A detailed experimentation," *Energies*, vol. 15, no. 22, p. 8450, 2022, doi: 10.3390/en15228450.

[14] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: Algorithm and applications," *Future Gener. Comput. Syst.*, vol. 97, pp. 849–872, Aug. 2019, doi: 10.1016/j.future.2019.02.028.

[15] M. Alonso, H. Amaris, J. Germain, and J. Galan, "Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms," *Energies*, vol. 7, no. 4, pp. 2449–2475, Apr. 2014, doi: 10.3390/en7042449.

[16] B. Aljafari, P. K. Balachandran, D. Samithas, and S. B. Thanikanti, "Solar photovoltaic converter controller using opposition-based reinforcement learning with butterfly optimization algorithm under partial shading conditions," *Environ. Sci. Pollut. Res.*, vol. 30, pp. 72617–72640, May 2023, doi: 10.1007/s11356-023-27261-1.

[17] C. Srithapon, P. Ghosh, A. Siritaratiwat, and R. Chatthaworn, "Optimization of electric vehicle charging scheduling in urban village networks considering energy arbitrage and distribution cost," *Energies*, vol. 13, no. 2, p. 349, Jan. 2020, doi: 10.3390/en13020349.

[18] T. U. Solanke, V. K. Ramachandaramurthy, J. Y. Yong, J. Pasupuleti, P. Kasinathan, and A. Rajagopalan, "A review of strategic charging–discharging control of grid-connected electric vehicles," *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101193, doi: 10.1016/j.est.2020.101193.

[19] S. Barshandeh and M. Haghzadeh, "A new hybrid chaotic atom search optimization based on tree-seed algorithm and levy flight for solving optimization problems," *Eng. Comput.*, vol. 37, no. 4, pp. 3079–3122, Oct. 2021, doi: 10.1007/s00366-020-00994-0.

[20] I. Pavić, H. Pandžić, and T. Capuder, "Electric vehicle based smart e-mobility system—Definition and comparison to the existing concept," *Appl. Energy*, vol. 272, Aug. 2020, Art. no. 115153, doi: 10.1016/j.apenergy.2020.115153.

[21] R. Devendiran, P. Kasinathan, V. K. Ramachandaramurthy, U. Subramaniam, U. Govindarajan, and X. Fernando, "Intelligent optimization for charging scheduling of electric vehicle using exponential Harris hawks technique," *Int. J. Intell. Syst.*, vol. 36, no. 10, pp. 5816–5844, Oct. 2021, doi: 10.1002/int.22531.

[22] X. Wang, C. Sun, R. Wang, and T. Wei, "Two-stage optimal scheduling strategy for large-scale electric vehicles," *IEEE Access*, vol. 8, pp. 13821–13832, 2020, doi: 10.1109/ACCESS.2020.2966825.

[23] E. Mouhcine, K. Mansouri, and Y. Mohamed, "Intelligent vehicle routing system using VANET strategy combined with a distributed ant colony optimization," in *Proc. Int. Conf. Adv. Inf. Technol., Services Syst.*, 2019, pp. 230–237, doi: 10.1007/978-3-030-11914-0_25.

[24] M. M. de Weerdt, S. Stein, E. H. Gerding, V. Robu, and N. R. Jennings, "Intention-aware routing of electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 5, pp. 1472–1482, May 2016, doi: 10.1109/TITS.2015.2506900.

[25] J. J. Q. Yu, W. Yu, and J. Gu, "Online vehicle routing with neural combinatorial optimization and deep reinforcement learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 10, pp. 3806–3817, Oct. 2019, doi: 10.1109/TITS.2019.2909109.

[26] Y. Kobayashi, N. Kiyama, H. Aoshima, and M. Kashiyama, "A route search method for electric vehicles in consideration of range and locations of charging stations," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 920–925, doi: 10.1109/IVS.2011.5940556.

[27] Y. Cao, N. Ahmad, O. Kaiwartya, G. Puturs, and M. Khalid, "Intelligent transportation systems enabled ICT framework for electric vehicle charging in smart city," in *Handbook of Smart Cities*. Cham, Switzerland: Springer, 2018, pp. 311–330, doi: 10.1007/978-3-319-97271-8_12.

[28] S. Das, A. Bhattacharya, and P. Acharjee, ''Charging scheduling of electric vehicles (EV) in probabilistic scenario considering grid-to-vehicle (G2V) and vehicle-to-grid (V2G),'' in *Proc. IEEE Calcutta Conf. (CALCON)*, Feb. 2020, pp. 467–472, doi: 10.1109/CALCON49167.2020.9106552.

[29] R. R. Kumar, C. Bharatiraja, K. Udhayakumar, S. Devakirubakaran, K. S. Sekar, and L. Mihet-Popa, ''Advances in batteries, battery modeling, battery management system, battery thermal management, SOC, SOH, and charge/discharge characteristics in EV applications,'' *IEEE Access*, vol. 11, pp. 105761–105809, 2023, doi: 10.1109/access.2023.3318121.

[30] T. N. Prasad, D. S. Muthubalaji, S. Srinivasan, B. Karthikeyan, R. Palanisamy, M. Bajaj, H. M. Zawbaa, and S. Kamel, ''Power management in hybrid ANFIS PID based AC–DC microgrids with EHO based cost optimized droop control strategy,'' *Energy Rep.*, vol. 8, pp. 15081–15094, Nov. 2022, doi: 10.1016/j.egyr.2022.11.014.

V. MANOJ KUMAR received the B.E. degree in electronics and communication engineering from Anna University, in 2010, and the M.Tech. degree in robotics from the SRM Institute of Science and Technology, Kattankulathur, Chennai, in 2012, where he is currently pursuing the Ph.D. degree. He is also an Assistant Professor with the Mechanical Engineering Department, SRM Institute of Science and Technology. His main research interests include robotics, machine learning in EV applications, charge scheduling, optimizations, and the Internet of Things.

BHARATIRAJA CHOKKALINGAM (Senior Member, IEEE) received the B.E. degree in electrical and electronics engineering from the Kumaraguru College of Engineering, Coimbatore, India, in 2002, the M.E. degree in power electronics and drives from the Government College of Technology, Coimbatore, in 2006, and the Ph.D. degree from the SRM Institute of Science and Technology, in 2015. He completed his first postdoctoral fellowship with the Centre for Energy and Electric Power, Faculty of Engineering and the Built Environment, Tshwane University of Technology, South Africa, in 2016, with National Research Foundation Funding. His second postdoctoral fellowship with the Department of Electrical and Computer Engineering, Northeastern University, Boston, MA, USA, where he was a Visiting Research Scientist, in 2018, and a Visiting Researcher with the University of South Africa, in 2019 and 2020. He is currently a Professor with the Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai, India, where he is also the Centre Head of the Centre for the E-Mobility. He is handling/handled government funded projects total worth Rs. 15.65 Cr, including SERB, DST, and TNSCST. He has authored more than 180 research papers and ten books chapters, and ten IPR patents in his name. He also made three technologies transfers. He is a Senior Member of IEI and IET. He is also a member, a mentor, and an advisor of many government and private companies bodies. He was a recipient of the DST, Indo-U.S. Bhaskara Advanced Solar Energy, in 2017, and the Young Scientists Fellowship, Tamil Nadu State Council for Science and Technology, in 2018. He was also a recipient of the World's Top 2% Scientists 2021 and 2022 in the Energy category. For more information visit the link: https://www.srmist.edu.in/faculty/dr-c-bharatiraja/.

LUCIAN MIHET-POPA (Senior Member, IEEE) was born in 1969. He received the bachelor's degree in electrical engineering, the master's degree in electric drives and power electronics, and the Ph.D. and Habilitation degrees in electrical engineering from the Politehnica University of Timisoara, Romania, in 1999, 2000, 2002, and 2015, respectively. Since 2016, he has been a Full Professor in energy technology with the Østfold University College, Norway. From 1999 to 2016, he was with the Politehnica University of Timisoara. He was also a Research Scientist with Danish Technical University, from 2011 to 2014, and also with Aalborg University, Denmark, from 2000 to 2002. He held a postdoctoral position with Siegen University, Germany, in 2004. He is also the Head of the Research Laboratory ''Intelligent Control of Energy Conversion and Storage Systems'' and he is one of the coordinators of the Master's degree Program in Green Energy Technology with the Department of Engineering, Østfold University College. He has published more than 200 papers in national and international journals and conference proceedings, and 15 books. He has served as a scientific and technical program committee member for many IEEE conferences. He has participated in more than 20 international grants/projects, such as FP7, EEA, and Horizon 2020. He has been awarded more than ten national research grants. His research interests include the modeling, simulation, control, and testing of energy conversion systems, and distributed energy resources (DER) components and systems, including battery storage systems (BSS) and BMS (for electric and hybrid vehicles), and energy efficiency in smart buildings and smart grids. He was invited to join the Energy and Automotive Committees by the President and the Honorary President of the Atomium European Institute, working in close cooperation with—under the umbrella—the EC and EU Parliament, and he was also appointed as the Chairperson of AI4People, Energy Section. Since 2017, he has been a Guest Editor of seven special issues of *Energies* (MDPI), *Applied Sciences*, *Majlesi Journal of Electrical Engineering*, and *Advances in Meteorology* journals.