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Optimal Scheduling of Electric Vehicle Charging at Geographically Dispersed Charging Stations with Multiple Charging Piles

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Abstract

The work presented in this paper deals with developing a charge scheduling strategy for electric vehicles in a predefined geographical region. Charging stations in the geographical region are considered to provide multiple charging levels with separate piles with an individual queue for each charging level. Assigning a charging station to each electric vehicle is considered as an optimization problem to minimize travel time, queue time, recharging time, and cost of energy for battery recharging. The objective function is constrained to the reachability of the electric vehicle with the available state of charge of the battery to the allotted charging station without violating the maximum permissible depth of discharge limit and allowable charging rate. The optimization model empowers the users to prioritize the function variable based on travel requirements and battery specifications in different case studies using the Opposition-Based Marine Predator Algorithm. This proposed algorithm is an improved version of the recently reported Marine Predator Algorithm in which the opposition-based learning mechanism is included to improve the solution accuracy. The solution obtained and the analysis of results show that the proposed strategy significantly reduces travel time, queue time, recharging time, and energy cost while fulfilling the constraints imposed.

Keywords Charge Scheduling · Charging Stations · Electric Vehicles · Marine Predator Algorithm (MPA) · Optimization

Nomenclature

SoC_i^{min}	Minimum permissible state of charge of the i^{th} vehicle battery
SoC_i^{max}	Maximum permissible state of charge of the i^{th} vehicle battery
DoD_i^{max}	Maximum permissible depth of discharge of the i^{th} vehicle battery
SoC_i^t	State of charge of i^{th} vehicle battery at time t
B_i	Nominal energy rating of the i^{th} vehicle battery (kWh)
ECR_i	Energy consumption rate (km/kWh)
d_{ij}	Distance between i^{th} vehicle and j^{th} charging station (km)
v_{ij}	Average velocity of i^{th} vehicle to reach j^{th} charging station (km/s)
t_{ij}	Driving time from i^{th} vehicle's current location to the j^{th} charging station (minutes)
d_{je_i}	Distance between j^{th} charging station and destination of i^{th} vehicle (km)
v_{je_i}	Average velocity of i^{th} vehicle from j^{th} charging station to reach the destination (km/s)
t_{je_i}	Driving time from j^{th} charging station to the i^{th} vehicle destination (minutes)
SoC_i^{req}	State of charge level required by the i^{th} vehicle battery
R_k	Charging rate in kW
$t_{c_{ik}}^t$	Time required to charge the battery of i^{th} vehicle at k^{th} charging pile (minutes)
$t_{q_{ik}}$	Queuing time for the i^{th} vehicle at k^{th} charging pile (minutes)
η_c	Charging efficiency
r_k	The price per unit of electricity in rupees
P_{ik}	Cost of electricity for charging i^{th} vehicle at k^{th} charging pile in rupees
$T_d(s_i)$	Total driving time of all the vehicles from present location to charging station and charging station to destination (minutes)
$T_w(s_i)$	Total waiting time of all the vehicles including queuing and charging time (minutes)
d_{is_i}	Distance between the current location and the allotted charging station of the vehicles (km)

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d_i^{max}	Maximum distance that the i^th vehicles can travel with the current SoC (km)
P_{is_i}	Total charging cost of all the vehicles in rupees
K_d, K_q, K_p	Priority indices for optimizing driving time, charging cost and queuing time respectively
K_{c1}, K_{c2}	Conversion factors for driving and queuing time respectively

1 Introduction

With growing concern about the environment and air pollution, Electric Vehicles (EVs) are seen as a potential replacement for conventional gasoline-powered vehicles to reduce fossil fuel consumption and emission of air pollutants [1]. Recent developments in electric vehicles have led to government policies to increase EV sales in the market [2]. Coordinated scheduling of EVs in the large fleet can be used to support the power system in load shaping [3, 4], voltage regulation, peak shaving [5, 6], and improving the reliability of the distribution system by operating as reserves [7, 8]. In addition, charge scheduling in accordance with time-based electricity tariffs has given rise to new profit-earning business opportunities [9–11]. Apart from these advantages, the penetration of EVs comes with more challenging tasks in the operation and control of the power system network. Random EV charging results in high peak demand, poor load factor, and frequent overloading of cables, transformers, and other components present in distribution and transmission systems [12, 13]. These challenges in the power system network can be overcome by vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technology, as discussed in [14, 15].

A simple charging station recommendation problem is formulated by Z. Tian et al. [16] in which vehicle has to decide whether to choose a nearer charging station or some other charging station with the less waiting time. The solution is obtained using an algorithm that considers a single vehicle at a time, calculates waiting time and travelling distance for each charging station from various options available, and then assigns the most suitable charging station. While the algorithm developed in this study fulfills the primitive objective of charging station assignment, it does not consider the effect of charging stations assigned to other vehicles while calculating the waiting time. Queuing models with iterative algorithms for the estimation of queue time are presented by Qin and Zhang [17]. The effect of charging station assignment to other vehicles is considered by considering the estimated future arrival rate and charging rate for EVs. Qin et al. consider only waiting time and do not consider the overall driving time from the existing location to the destination. A scheduling algorithm with stochastic modeling of queuing time is proposed by Gusrialdi et al. [18]. Waiting time at various charging stations within reach depending upon the current battery charge of EVs traveling on a specific route is calculated. The scheduling algorithm carries out the charging station assignment using local information at various distributed control centers. The coordination is maintained through communication among various distributed controls to minimize the waiting time at all charging stations with better system performance [19]. An algorithm using a modified search method is proposed by Razo et al. to obtain the optimal charging stations (CSs). These works deal with CSs along a predefined traveling path and do not consider those along potential alternative paths.

Charge scheduling strategies require global information in addition to the local information because the local information contains only vehicle location, State-of-Charge (SoC), and CS; therefore, algorithms based on this information cannot estimate the queuing time. To resolve this issue, a strategy of communication among vehicles is proposed by Shun-Neng Yang et al. [20] in order to obtain global information to estimate queuing status at all CSs. The work shows that vehicle scheduling with algorithms based on global information is superior to using only local information. Charge scheduling strategy for EVs to minimize the cost of recharging and travelling time is discussed by Sweda and Klabjan [21]. Travelling time along with recharging costs are calculated for every vehicle on different possible paths. Problem is formulated as dynamic programming, and the optimal solution is obtained, but this work does not consider the waiting time at charging stations. Optimal allocation of CSs considering travelling time, recharging time, and waiting time are proposed by T. Guo, You, and Yang [22]. Waiting time is planned based on the number of EVs previously waiting at CSs, expected arrival of EVs, and average recharging time for each vehicle. Game theory is used for solving the problem, but the work does not consider SoC limits and the cost of recharging batteries. A charging strategy for EVs with optimum charging cost, travelling time, and waiting time is proposed by Moghaddam et al. [23]. The work considers multiple piles with different charging rates at each CS and considers SoC levels of batteries; however, the work calculates waiting time based on the probability of arrival and departure of vehicles instead of actual data obtained through communication among vehicles and charging stations [24, 25].

The above literature study shows that very few studies utilize heuristics algorithms for CSs schedules. Recently, many researchers have reported various metaheuristic algorithms to solve real-world, constrained optimization problems. Since charge scheduling is considered as an optimization problem, the EV system requires a more feasible optimization algorithm. Many single-objective optimization algorithms, such as particle swarm optimizer (PSO) [25], ant colony optimizer (ACO) [26], grey wolf optimizer (GWO)

[27], whale optimization algorithm (WOA) [28], salp swarm algorithm (SSA) [29], sine–cosine algorithm (SCA) [30], moth flame optimizer (MFO) [31], equilibrium optimizer (EO) [32], marine predator algorithm (MPA) [33], slime mould optimizer (SMA) [34], gradient-based optimizer (GBO) [35], etc. are reported in the literature. EO is a recent algorithm proposed in 2020 based on control volume mass balance models used to estimate both dynamic and equilibrium states. Here search agents are the particles that update their concentration based on the instantaneous best solution to attain the equilibrium state known to be the optimal solution. MFO algorithm is one of the fine meta-heuristic optimization algorithms proposed in 2015. The main inspiration of MFO came from the navigation method of moths in nature called transverse orientation. SCA is a meta-heuristic algorithm inspired by the features of trigonometric sine and cosine functions proposed in 2016. WOA is a nature inspired meta-heuristic optimization algorithm inherited from the bubble-net hunting strategy of humpback whales proposed in 2016. Its exploitation phase includes shrinking encircling mechanism and spiral updating position. GWO is bio-inspired algorithm based on the interesting fact of social hierarchy and hunt mechanism of wolves proposed in 2014. This imitates the dominance hierarchies for the search agents where the wolves are empowered according to their strength and power. GBO is a new meta-heuristic optimization method proposed in 2020 that is inspired by the gradient-based Newton's method. Gradient search rule enhances the exploration tendency and accelerate the convergence rate to achieve better positions in the search space whereas local escaping operator enables optimizer to escape from local optima. MPO is a nature-inspired optimizer based on the behavior of predator and prey with levy and Brownian movement in the marine ecosystem proposed in 2020.

These algorithms explore their superiority in handling numerical problems and real-world problems with and without inequality and equality constraints. As per the No-Free-Lunch theory, none of the algorithms can solve all optimization problems [36]. This theory motivates the researchers to develop new or improved versions of existing algorithms to handle real-time optimization problems with constraints. This paper introduces an improved version of the Marine Predator Algorithm (MPA) based on the opposition-based learning mechanism called Opposition-Based Marine Predator Algorithm (OBMPA) for CS scheduling. The proposed OBMPA is derived from the basic version of MPA, and the inspiration of MPA is a foraging approach called Brownian and Levy movement in marine predators with the best hunting rate in biological communication between the prey and predator.

When an EV needs recharging of its battery while travelling, it may not always be the most suitable option to drive to the nearest CS as there can be other potential alternatives where queue length is very small and thus waiting time is significantly less. Overall, travelling time is reduced, although the vehicle has to travel to CS located at a longer distance in cases where the waiting time is substantially less than that at the nearest charging station. The recharging cost is different at various CSs, and the assignment of CS to EVs should consider the desired trade-off between recharging cost and travelling time. This paper presents a coordination strategy to assign a charging station to each EV member requesting a charge. The strategy ensures optimum driving time from the current location to CS, waiting time in queue, recharging time, and driving time from CS to destination. The waiting time is calculated based on charging rate and SoC data of EVs already waiting at CSs and vehicles that are approaching the CSs for recharging. A dedicated queue for each of multiple charging piles with different charging rates is considered to calculate waiting time and recharging time at each charging pile. This paper also considers minimizing recharging costs associated with energy consumption for battery charging. Vehicle assignment makes sure that the assigned CS for every vehicle is within its reach depending on current battery SoC, maximum permissible Depth-of-Discharge (DoD), distance to be traveled by vehicle, and vehicle energy consumption rate during driving. The strategy gives EV users to decide while making a charging request whether the higher priority is given to waiting time or to the cost of recharging. The main contributions of the paper are as follows.

- Formulation of the new objective function by considering the driving time to CS, queuing time, charging time, and driving time to destination with monetary benefits.
- Assignment of CS based on current SoC, maximum allowable DoD, distance travelled, and energy consumption rate.
- Assignment of charging piles using an improved version of the marine predator algorithm called OBMPA and the strategy for waiting time calculation.
- Seven different case studies, such as total time, total cost, electrical pricing, queuing and charging time, driving time alone, destination time alone, and combination of driving time, queuing time, and charging time, are considered to validate the system performance.
- The performance of OBMPA is compared with other state-of-the-art algorithms in terms of priority indices based on time and cost with and without coordination strategy and queuing time with and without coordination strategy.

The remainder of the paper is structured as follows: The model of a system containing electric vehicles and charging infrastructure is discussed in Section 2. The objective function for optimization is also developed in this section.

Overview of the proposed charge scheduling strategy is presented in Section 3. Algorithms for calculating distances, waiting time, and obtaining an optimal solution for the problem of charging station assignment are discussed in this section. Simulation results for all case studies are comprehensively presented in Section 4. Section 5 discusses the performance analysis of the proposed algorithm and comparison with other selected algorithms. Finally, the conclusion of the work is presented in Section 6.

2 Problem Formulation

Consider the EVs in a particular geographical location need to be allotted with the CSs incorporating mandatory and user-customized constraints. Figure 1 illustrates the overall problem formulation for scheduling of EV charging at geographically dispersed CSs with multiple charging pile. Each CS has multiple charging piles with different charging rates, separate queues, and a distinct price for recharging. The monetary cost paid for recharging the vehicle battery depends on the charging rate at the pile where it is being recharged. Queue length at each charging pile is mainly influenced by recharging the time of individual vehicles and the arrival rate of vehicles to that particular charging pile. Information such as vehicle location, battery data, charge rates, and price details of charging stations can be directly obtained from real-time communication with vehicles and charging stations. The following data is transferred and processed for obtaining the objective function to be minimized.

- Battery capacity and maximum permissible DoD of each vehicle
- Battery SoC of each vehicle at the time of charging request
- Desired SoC till which individual electric vehicle is to be charged
- Every EV energy consumption rate
- Number of CSs in the geographic area
- Positions of CSs in terms of the coordinate positions
- Destinations and current location of the EV demanding a charge
- Average EV speed on roads from the current location of each EV to every CS
- Average EV speed on roads from every CS to the destination of each EV
- Number of charging piles at every CS and maximum rate of charging at each pile

2.1 EV range with Current State-of-Charge (SoC)

The minimum permissible SoC of the battery (SoC_i^{min}) i^{th} vehicle is written as

$$SoC_i^{min} = SoC_i^{max} - DoD_i^{max} \tag{1}$$

where SoC_i^{max} denotes the maximum permissible SoC rate of the i^{th} vehicle battery and DoD_i^{max} denotes the maximum permissible DoD rate of the i^{th} vehicle battery. If SoC_i^t is the level of SoC of i^{th} vehicle battery at time t then maximum distance travel by the vehicle with the current SoC is given in Eq. 2.

$$d_i^{max} = B_i \times \frac{SoC_i^t - SoC_i^{min}}{100} \times \frac{1}{ECR_i} \tag{2}$$

where ECR_i denotes the rate of energy consumption in km/kWh and B_i denotes nominal energy rating in kWh of the i^{th} vehicle battery.

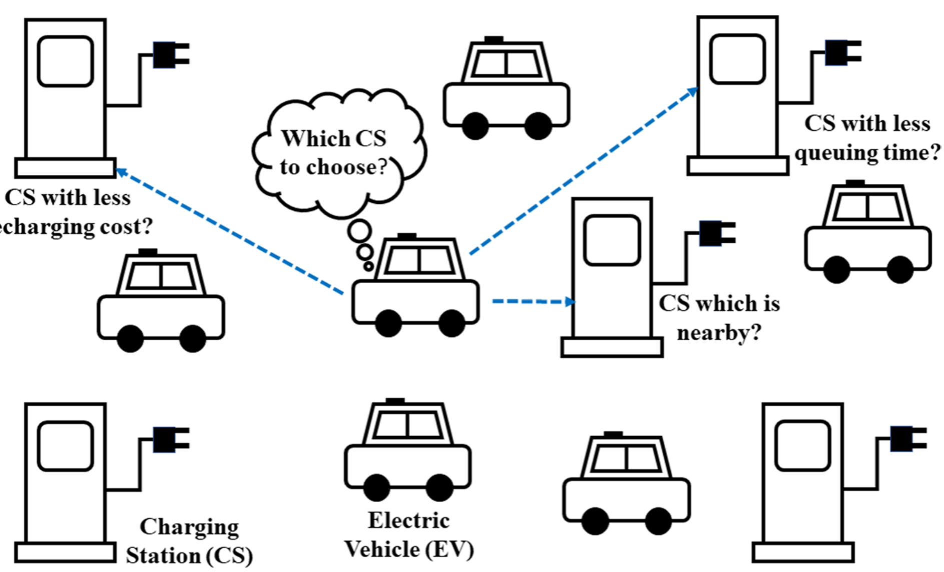

Fig. 1 Overall impression of the proposed scheduling strategy

2.2 Driving Time

The driving time from i^{th} vehicle's current location to the j^{th} CS is

$$t_{ij} = \frac{d_{ij}}{v_{ij}}, j \in \mathbb{J}, i \in \mathbb{I}(t) \quad (3)$$

The driving time from j^{th} CS to the i^{th} vehicle destination is expressed as follows.

$$t_{je_i} = \frac{d_{je_i}}{v_{je_i}}, j \in \mathbb{J}, i \in \mathbb{I} \quad (4)$$

where $\mathbb{J}$ denotes all CS set in a geographic area, $\mathbb{I}$ denotes all candidate vehicles set for charging, v_{ij} denotes vehicle's average velocity to travel from i^{th} EV to j^{th} CS, d_{ij} denotes the distance between i^{th} EV to j^{th} CS, d_{je_i} denotes the distance between j^{th} CS and destination of i^{th} EV, and v_{je_i} denotes average traffic velocity to travel from j^{th} CS and destination of i^{th} EV.

2.3 Charging Time

When EV is plugged in at instant t, the time required to charge the battery of i^{th} EV at k^{th} charging pile is given in Eq. 5.

$$t^t_{c_{ik}} = \frac{\left(SoC^{req}_i - SoC^t_i\right) \times B_i}{R_k \times 100} \quad (5)$$

where SoC^{req}_i denotes the required SoC in % till which battery of i^{th} EV is to be charged, SoC^t_i denotes the SoC of battery in % for i^{th} EV at time t, B_i denotes the nominal energy capacity of i^{th} EV in kWh, and R_k is the rate of charging in kW at the k^{th} charging pile.

2.4 Queuing Time

If the k^{th} pile present in the j^{th} charging station is assigned to the i^{th} vehicle, then the i^{th} vehicle's queuing time is given in Eq. 6.

$$t_{q_{ik}} = \begin{cases} \sum_{i\epsilon\mathbb{I}^t_k} t^t_{c_{ik}} + \sum_{i\epsilon\mathbb{I}^{t,T}_k} t^{\mathrm{T}}_{c_{ik}} - t_{ij}, \text{if} t_q > 0 \\ 0, if t_q \le 0 \end{cases} \quad (6)$$

where T is equal to $t + t_{ij}$, $\mathbb{I}^t_k$ denotes the set of all vehicles already waiting at k^{th} charging pile, and $i\epsilon\mathbb{I}^{t,T}_k$ denotes the set of all vehicles arriving during the interval (t,T) at the k^{th} charging pile.

2.5 Charging Cost

The cost of electricity for charging i^{th} EV at k^{th} charging pile is given in Eq. 7.

$$P_{ik} = \frac{t^t_{c_{ik}} \times R_k}{\eta_c \times 100} \times r_k = \frac{\left(SoC^{reg}_i - SoC^t_i\right) \times B_i}{\eta_c \times 100} \times r_k \quad (7)$$

where R_k charging rate in kW at k^{th} charging pile, η_c denotes charging efficiency, and r_k is the price per unit in rupees of electricity consumed.

2.6 Formulation of the Proposed Objective Function

The proposed strategy for charging has to fulfill the following objectives by assigning charging station and pile to every EV demanding to charge:

- The total travelling time of every electric vehicle is to be minimized
- The waiting time of each vehicle is to be minimized such that queues at charging stations are reduced
- The charging station allocated to individual EV is near to the path of travel from the current location to the destination
- The monetary cost of recharging the battery of each vehicle is minimized
- The desired trade-off between queuing time and recharging cost is obtained depending on the priority given during charge request by the vehicle user

Let $\vec{s}$ be the vector of any feasible grouping for provision of charging piles to candidate electric vehicle where $s_i = k$ means a plan of assigning i^{th} vehicle to k^{th} charging pile while $\alpha(k) = j$ means that the k^{th} charging pile lies in the j^{th} charging station. For example, $s_2 = 5$ means the 5^{th} charging pile is assigned to the 2^{nd} EV and $\alpha(5) = 3$ means that the 5^{th} charging pile is at the 3^{rd} charging station. The equation representing the proposed model for obtaining an optimal solution is given as

$$C_i(\vec{s}) = K_{c1} \times K_d \times T_d(s_i) + K_{c2} \times K_q \times T_w(s_i) + K_p \times P_{is_i} \quad (8)$$

The main/primary objective function considering all possible terms of optimization can be written as

$$\text{Minimize} : f_1 = \sum_i C_i(\vec{s}) \quad (9)$$

Individual terms of the Eq. 9 associated with each electric vehicle are given by Eq. 8.

$$T_d(s_i) = t_{i\alpha(s_i)} + t_{\alpha(s_i)e_i} \tag{10}$$

$$T_w(s_i) = t_{q(s_i)}^{\;t+t_{is_i}} + t_{ci(s_i)}^{t} \tag{11}$$

constrained to

$$d_{is_i} < d_i^{max} \tag{12}$$

Where T_d is the sum of driving time required to travel from the current location to the assigned charging station and driving time from the charging station to the electric vehicle destination as mention in Eq. 10, minimization of this term contributes to a reduction in overall travel time. T_w is the sum of waiting time in the queue at the charging pile and recharging time as given in the Eq. 11. Minimizing this term for every vehicle result in reduced queue length at charging stations compared to that in uncoordinated charging. The driving, charging and waiting time are considered in minutes. The constraint in Eq. 12 ensures that the EVs can reach the assigned CSs with the available SoC. The term d_{is_i} denotes distance between the current location of the ith EV and the allotted charging station whereas d_i^{max} is the maximum distance that EV can travel. P_{is_i} is associated with charging cost, which optimizes the monetary cost incurred on energy consumption for battery charging. K_{c1} and K_{c2} are the conversion factors for driving and queuing time to match the weight of charging price in the cost function. K_d, K_p and K_q are positive coefficients that are priority indices for optimizing driving time, charging cost and queuing time, respectively.

3 Proposed Opposition-Based Marine Predator Algorithm (OBMPA)

This section of the paper briefly introduces the basic version of MPA and explains the formulation of new OBMPA based on Opposition-Based Learning.

3.1 Basic Marine Predator Algorithm (MPA)

The MPA is a new technique for optimization and is guided by the characteristics of the prey and predator in specific [33]. The initial MPA solution is uniformly distributed in the search space instead of the initialization steps of several other heuristic algorithms. Equation 13 presents the initialization phase of MPA.

$$X_0 = X_{lb} + rand(X_{ub} - X_{lb}) \tag{13}$$

where X_{lb} and X_{ub} are the lower and upper bounds of the design variables, and *rand* denotes the random

Stage 1: When the prey moves faster, the predator establishes a waiting approach, tracking the prey's motion from the location. Equation 14 is the position update formula of the prey.

$$SP_i = R_B \otimes (Elite_i - R_B \otimes Prey_i), i = 1, \ldots, n \tag{14}$$

$$Prey_i = Prey_i + P.R \otimes SP_i \tag{15}$$

Where $\otimes$ denotes element-wise multiplication, R_B denotes vector comprising normal distributed random numbers on behalf of the Brownian movement, P denotes a constant number and is equal to 0.5, and R denotes a uniform distributed random vector between [0,1]. In addition, SP_i denotes the i^{th} prey's step size during the next move. Brownian movement of prey is imitated by multiplying *Prey* by R_B.

Stage 2: The predator and the prey are moving around at the same pace in this stage, with the predator adopting the Brownian movement and the prey following the Lévy movement.

$$\begin{gathered} SP_i = R_L \otimes (Elite_i - R_L \otimes Prey_i), i = 1, ..., n/2 \\ Prey_i = Prey_i + P.R \otimes SP_i \end{gathered} \tag{16}$$

where R_L denotes random number vector which imitates Levy's movement, and the Levy movement of the prey is imitated by multiplying *Prey* by R_L. Equation 16 is accountable for the exploration during the first half, and Eq. 17 is accountable for the second half exploitation. *CF* denotes an adaptive parameter.

$$\begin{gathered} SP_i = R_B \otimes (R_B \otimes Elite_i - Prey_i), i = n/2, ..., n \\ Prey_i = Elite_i + P.CF \otimes SP_i \end{gathered} \tag{17}$$

Stage 3: In this stage, the predator moves faster than the prey, and the Lévy movement is the predator's approach. The update formula of the predator position is shown as follows.

$$\begin{gathered} SP_i = R_L \otimes (R_L \otimes Elite_i - Prey_i), i = 1, \ldots, n \\ Prey_i = Elite_i + P.CF \otimes SP_i \end{gathered} \tag{18}$$

3.1.1 Effect of FADs and Eddy Formulation

For instance, the existence of eddy currents and the operation of fish aggregating devices (FADs) would alter the predatory behavior of predators. This behavior of this effect can be mathematically modelled as follows.

$$Prey_i = \begin{cases} Prey_i + CF[X_{lb} + R \otimes (X_{ub} - X_{lb})] \otimes U & if\ r \le FADs \\ Prey_i + [FADs(1-r) + r](Prey_{r1} - Prey_{r2}) & if\ r > FADs \end{cases} \tag{19}$$

where r denotes the random number between [0,1], X_{lb} and X_{ub} denote vectors comprising the lower and upper limits of the design variables, U denotes binary vector, and if the random solution is larger than 0.2, the value is 1, if the random solution is smaller than 0.2, the value is 0, r_1 and r_2 denote random directories of the prey matrix and $FADs = 0.2$.

3.2 Opposition-Based Learning (OBL) Scheme

Nature-inspired techniques usually begin with a random solution and attempt to find the best solution under the predefined requirements for termination. The searching process ends when the termination conditions are met or the solution is stuck in a local optimum. The quest in both ways (random and its opposite direction) offers a greater opportunity to seek the uncertain optimum of the problem in OBL. When the optimal locations are in the opposite direction of an established solution, the OBL is quite beneficial. An OBL process is then inserted into the recently reported MPA in this paper to step out of local optima when inactivity exists and investigate the more capable areas of the search space [37]. The description of the OBL process and opposite numbers used in MPA is stated as follows.

3.2.1 Opposite Numbers

In this framework, the solution and its opposite solution are suggested to improve the search strategy. It is proposed in [38, 39] that, by following the theory of opposite numbers, the computation time might be reduced. As follows, the opposite number can be described. Consider $\boldsymbol{x} \in \boldsymbol{R}$ to be a number lying in [a, b] interval, then the respective opposite number x' is determined as follows.

$$x' = lb + ub - x \tag{20}$$

where lb and ub denote lower and upper limits of the decision variable x. The same approach is extended to the vectors of R_d as follows. Consider $X = (x_1, x_2, \ldots, x_d) \in R_d$ is a point in a d-dimensional space and the respective opposite point $X' = (x_{1'}, x_{2'}, \ldots, x_{d'})$ is determined as follows.

$$x'_i = lb_i + ub_i - x_i \tag{21}$$

where $\mathrm{I} = 1, 2, \ldots, d$ and lb and ub denote the lower and upper bounds of x_i.

3.2.2 Application of OBL in MPA

A stable and high-performance optimization technique to solve various engineering challenges is the traditional MPA. However, no algorithm is ideal for handling all optimization problems utilizing the No-Free-Lunch theory. Consequently, this paper recommended one significant change for MPA to escape the constraints of MPA, to a certain degree, and to boost its abilities in managing CS allocation for Evs demanding to charge. In addition, the OBL strategy improves the diversity of the population at the initialization stage.

***Algorithm 1*: Pseudocode of OBMPA**

```
Start: Initialize search agents and random initial solution
       Determine the best opposite solutions using OBL scheme, then choose
       the suitable solutions using Eq. 28.
       While termination criteria are not met
             Calculate the value of fitness, formulate Elite matrix and do
             memory saving
             If Iter<Max_Iter/3
                   Update prey using Eq. 14 and Eq. 15
             Else if Max_Iter/3<Iter<2*Max_Iter/3
                   For the first half of the populations
                   Update prey using Eq. 16
                   For the other half of the populations
                   Update prey using Eq. 17
             Else if Iter>2*Max_Iter/3
                   Update using Eq. 18
             End If
             Achieve memory saving and Elite update
             Put on effects of FADs and update using Eq. 19
       End While
End
```

The implementation procedures of the suggested OBMPA are presented below.

Step 1: Initialize the population X randomly, with a size of N
Step 2: Put on the OBL scheme and produce opposite solutions, then choose the suitable solutions
Step 3: Execute the MPA to update the population position of each individual and find the optimal current position as per the best value of the fitness
Step 4: Execute the next iteration in MPA. Compare the current best solution and potential solution.
Step 5: Repeat from Step 2 until the termination criteria

The pseudocode of the proposed OBMPA is presented in Algorithm 1.

3.3 Scheduling Strategy

3.3.1 Overview of Proposed Strategy

The prerequisite information is needed in real-time in order to obtain the solution for a specified problem. This data comprises vehicle locations, battery SoC and capacity, required SoC level till which battery is to be charged, the energy consumption rate of the vehicle, prices at various charging stations, maximum charging rate supported by each pile in every charging station, average vehicle velocities for vehicles at various paths. This information is regularly updated while initializing the algorithm for the optimal solution. Charging stations within reach of each electric vehicle that constitute the set of feasible solutions are determined from data collected using a simple algorithm. Distances among all possible charging stations and electric vehicles requesting recharging are calculated using location data.

In contrast, the maximum distance that each vehicle can travel is calculated using the present battery SoC and the energy consumption rate of the vehicle. This information is loaded in an optimization algorithm that updates the solution in each iteration. The maximum charging rate permissible for every vehicle battery is compared with the maximum charging rate of the allotted charging pile. The recharging rate is decided such that it does not exceed the maximum permissible value specified for the individual battery. Solution parameters, total time, waiting time, the recharging cost are updated in the optimization algorithm, and this iterative process is repeated until the solution converges to an optimum value. The flowchart for the overall scheduling strategy using the proposed OBMPA is shown in Fig. 2.

3.3.2 Calculation of Waiting Time

Waiting time for a vehicle at the charging pile is calculated based on recharging time taken by each vehicle in the queue ahead of the vehicle under consideration when it arrives at the charging station. In addition, electric vehicles which are not currently waiting in queue but will be arriving at the charging pile assigned to a particular vehicle before it reaches for recharging are also taken into account. Finally, the queue is modelled, and the waiting time is calculated using Algorithm 2.

***Algorithm 2*: For Waiting Time Calculation**

Input: $\vec{s}$, t_{ij}, $\sum_{i\epsilon \mathbb{I}_k^t} t_{cik}^t$
Output: t_q

Initialization: $t_q = \begin{cases} \sum_{i\epsilon \mathbb{I}_k^t} t_{cik}^t + \sum_{i\epsilon \mathbb{I}_k^{t,T}} t_{cik}^{\mathrm{T}} - t_{ij}, & \text{if } t_q > 0 \\ 0, & \text{if } t_q \le 0 \end{cases}$

```
For i = 1:Number of EVs do
    For m = 1:Number of EVs do
        If s(m) = s(i) and t_mα(s_i) < t_iα(s_i)
            t_q(i) = t_q(i) + t_cm(s_i)
        Else
            t_q(i) = t_q(i)
        End If
    End For
        If t_q < 0 Then
            t_q = 0
        End If
End For
Return t_q
```

3.3.3 Optimal Solution using the Proposed OBMPA

Each of the charging piles in a geographical area is identified with a numeric tag given to it. Evs and CSs are associated with similar distinct numeric tags. The solution for the problem of optimal allocation of charging piles to EVS giving charge request in a prescribed time slot is represented by a vector $\vec{s}$ in which each i^{th} component s_i of this vector is a numeric tag associated with the charging pile assigned to the i^{th} vehicle. If the geographical region has N number of charging piles with d EVs giving a charge request, the solution is obtained as shown in Eq. 22.

$$\vec{s} = \left[s_1, s_2, ..., s_d\right] \tag{22}$$

Any element of this solution vector $s_i = k$ means k^{th} charging pile is assigned to i^{th} EV, thus $\vec{s}$ is an array of length d with and each element of this array can take N distinct values. The proposed opposition-based marine predator algorithm in which random uniform populations are generated to search optimum solutions within a specified search area is used to obtain the solution. The search area for OBMPA in this particular problem is d-dimensional space with each axis of length N units. The solution set consists of N^d unique points, making a number of feasible candidate solutions grow exponentially with an increase in the number of EVs requesting the charge; therefore, an adequate initial population of particles is needed to ensure sufficient sampling in solution space. Since the domain of objective function being discrete can take only integer values, the populations cannot move smoothly along search space as in the case of continuous one but can only jump from one possible position to any other within a set of feasible N^d positions. Algorithm 3 presents the overall scheduling strategy using the proposed OBMPA.

***Algorithm 3*: OBMPA for Proposed Strategy**

Input: d_{ij}, V_{ij}, d_{je}, V_{je}, SoC_i^{reg}, SoC_i^t, R_k, ECR_i, and r_k
Output: $\vec{s}$

Initialization: Iteration counter t=0
Random population generation; Determine the best opposite solutions using OBL scheme, then choose the suitable solutions

Step 1: $\forall m$, $\overrightarrow{x_m}$=rand(1, Q)
Step 2: Update best position and cost for initialized population
Step 3: **For** each population **do**
  Individual Best Cost, $\sum_i = C_i(\overrightarrow{x_m})$
  Individual Best Position, $\overrightarrow{x_m}$
End For
Step 4: Best Cost, min(C_m)
Best Position, $\overrightarrow{x_m}$
Step 5: Update population position for next iteration using Eq. 16 - Eq. 19
Step 6: Update best position and cost values
Step 7: **For** each population **do**
  $C_m(t+1) = \sum_i = C_i(\overrightarrow{x_m}(t+1))$
  If $C_m(t+1) \leq C_m(t)$ **then**
    Individual Best Cost $= C_m(t+1)$
    Individual Best Position=$\overrightarrow{x_m}(t+1)$
  Else
    $C_{mbest} = C_m(t)$
    $x_{mbest} = x_m(t)$
  End If
End For
Step 8: Best Cost, min(C_{mbset})
Best Position, $\overrightarrow{x_{mbest}}$
Step 9: Increment t=t+1
Step 10: **If** a<a_{max} **then**
  Repeat from Step 5
Else
  Calculate all solution parameters
End If
End

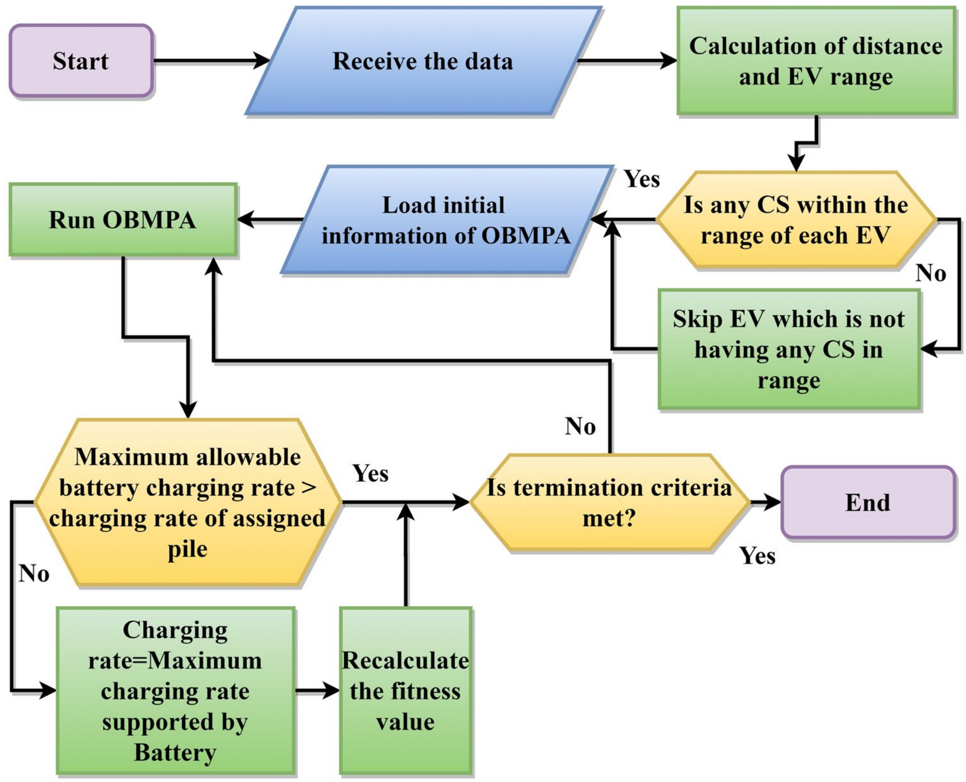

Fig. 2 Flowchart illustrating the proposed strategy for assignment of charging piles

4 Simulation Results and Discussions

This section discusses the results obtained by the proposed OBMPA and other selected algorithms, such as EO, MFO, SCA, WOA, GWO, GBO, and the basic MPA. The comparison between the proposed algorithm and other algorithms is also made to validate the performance of all algorithms while handling the charging scheduling optimization problem. The results have been obtained for the objective function, as discussed in Section 2, of geographical area with the rectangular shape of dimensions 50 × 50 km with eight charging stations and 18 electric vehicles requesting a charge in case study I. Case study II considers 24 electric vehicles and 12 charging stations in the same geographical area. It has been considered that each CS has two charging piles with different charging rates.

Table 1 Parameter settings of all algorithms

S. No	Algorithm	Control Parameters	Value
1	EO	a_1, a_2, and RP	2, 1, and 0.5, respectively
2	MFO	a	Linearly decreases from -1 to -2
		b	1
3	SCA	a	2
		r_1	Linearly decreases from a to 0
4	WOA	a	Linearly decreases from 2 to 0
		a_2	Linearly decreases from -1 to -2
		b	1
5	GWO	a	Linearly decreases from 2 to 0
6	GBO	P_r	0.5
7	MPA & OBMPA	*FADs*, Mutation probability, and p	0.5

Table 2 Priority indices of all EVs for all test case study I

EV	EV-1	EV-2	EV-3	EV-4	EV-5	EV-6	EV-7	EV-8	EV-9
K_d	**1**	**1**	**1**	**1**	**3**	**2**	**1**	**1**	**2**
K_p	2	1	1	1	1	2	1	2	1
K_q	1	1	1	1	2	1	1	1	1
EV	EV-10	EV-11	EV-12	EV-13	EV-14	EV-15	EV-16	EV-17	EV-18
K_d	**2**	**1**	**2**	**3**	**1**	**1**	**1**	**1**	**1**
K_p	1	1	2	1	2	1	1	2	1
K_q	1	1	2	1	3	2	3	1	1

The control parameters of all selected algorithms are listed in Table 1. The population size is selected as 60, and a maximum number of iterations is selected as 3000 for all selected algorithms. For a fair comparison, all algorithms are executed 30 times individually, and the statistical result analysis is also carried out in the subsequent section of this paper. All algorithms are implemented in the MATLAB2020b simulation platform, and algorithms are executed on the same laptop.

4.1 Case Study-1

As discussed earlier, case study-I minimizes charging cost, driving time, queueing time, and electricity pricing for 8 charging stations and 18 electric vehicles. The priority indices are very important while optimizing the selected case study objective function. The values of K_d, K_p and K_q are listed in Table 2 for optimizing driving time, charging cost and queuing time, respectively. The values of K_{c1} and K_{c2} are tuned to be 3 by considering weightage of driving time, queuing time and charging price towards the cost function. Based on K_d, K_p and K_q values, the charging piles are assigned to the vehicle by considering minimization of charging cost than queuing time when $K_p > K_{q,}$ K_d or minimization of driving time when $K_d > K_{q,}$ K_p or minimization of queuing time than recharging cost when $K_q > K_{p,}$ K_d. This is true for all case studies. The results obtained by the proposed OBMPA and other algorithms for case study-I are analyzed in this sub-section. The charging station allocation to each EV without and with priority indices is illustrated in Fig. 4 for case study I. The location of the CSs in the

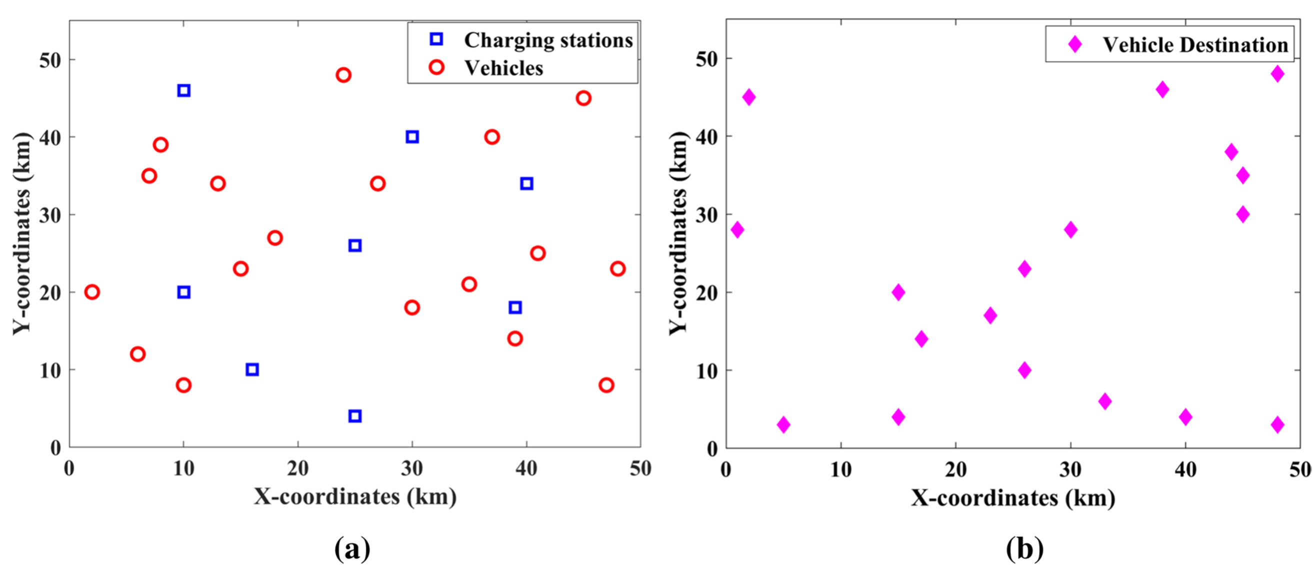

Fig. 3 Position of the CSs and electric vehicles for case study I

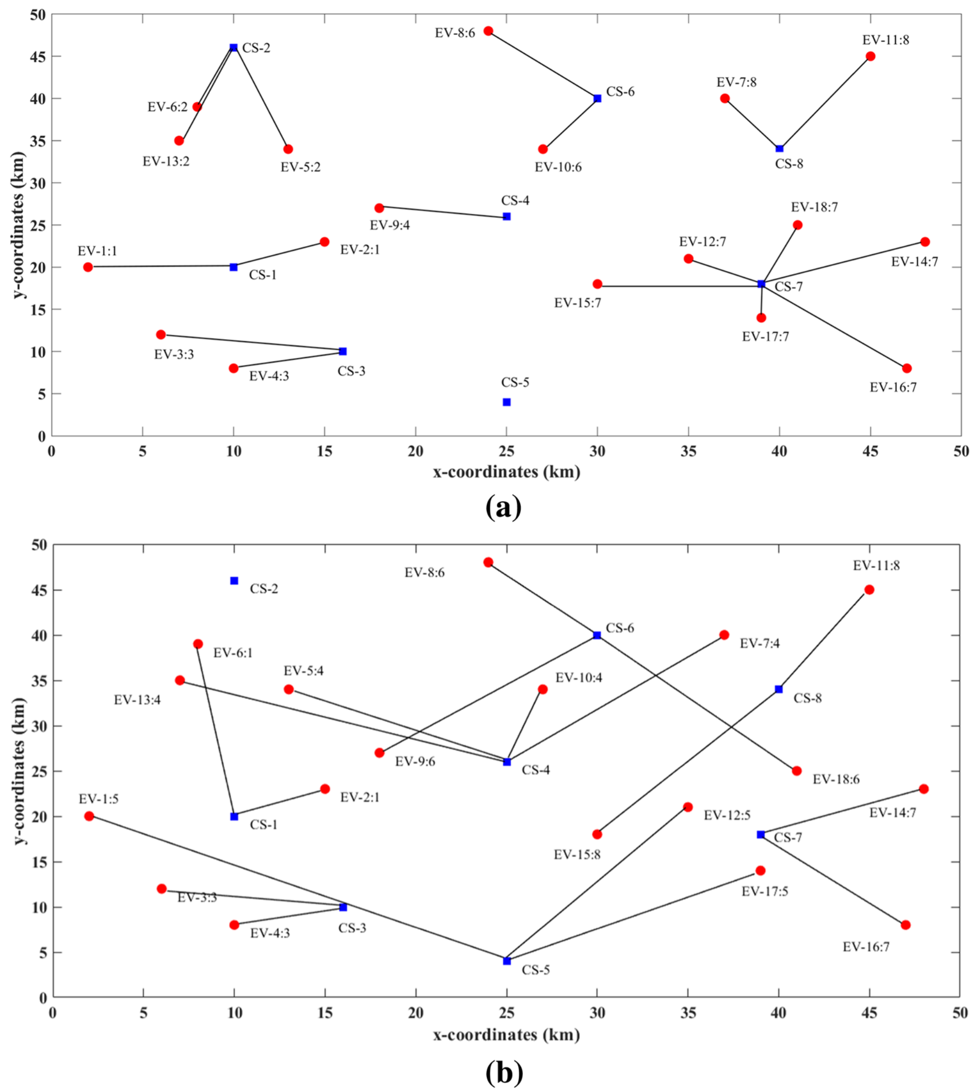

Fig. 4 Charging station allocation for all EVs; (**a**) Without priority indices, (**b**) With priority indices by the OBMPA for CS-I

geographical region under consideration and current locations of EVs requesting battery recharging is shown in Fig. 3a, while the destination of vehicles requesting charging is indicated in Fig. 3b.

An analytical method is considered to simulate the behavior during uncoordinated charging, which assigns fast charging pile of the nearest CS to every EV. The charging station allotment is shown in Fig. 4a. It can be seen that one of the CSs, i.e., CS-5 is unassigned since no vehicle is approaching it, and some of the CSs are overcrowded, especially CS-7 is assigned with 6 EVs. The proposed strategy addresses this problem as it is evident from Fig. 4b that each charging station has been allotted with the EVs based on the user priority to choose among driving time, queuing time and charging cost for minimizing the objective function for a better utilization of charging infrastructure. Table 3 shows the obtained solutions by the proposed OBMPA. It is evident from Table 3 that the charging station allocated to each electric vehicle is within its range considering present SoC, and thus, DoD constraints for batteries of all vehicles are satisfied. The boldface in all tables indicates the best result.

From Table 3, it is observed that the total time taken by all 18 EVs is equal to 1137.184 Min., and the total charging cost of all 18 EVs is equal to Rs. 3007.624/-. Total time is the sum of driving time from the current location to the assigned CS ($\boldsymbol{t}_{i\alpha(s_i)}$), waiting time in the queue and battery recharging time ($T_w(s_i)$), and driving time from the CS to the destination of the EV ($\boldsymbol{t}_{\alpha(s_i)e_i}$). Table 3 shows the CS station allotment with the charging pile number. It also lists the distance traveled by each EV with an existing SoC to

Table 3 Solution and parameters obtained by the proposed OBMPA for Case Study-I

EV	CS	Pile	$t_{i\alpha(s_i)}$ in Min	$T_w(s_i)$ in Min	$t_{\alpha(s_i)e_i}$ in Min	Total time in Min	Charging cost in Rs	Range with current SoC in Km	Distance from assigned CS in Km
1	5	10	32.328	58.951	28.287	119.566	196.627	31.129	28.018
2	1	1	6.479	22.440	29.165	58.084	204.765	33.782	5.831
3	3	6	11.767	18.709	28.320	58.796	110.103	31.231	10.198
4	3	5	6.543	13.492	37.996	58.030	124.467	34.133	6.325
5	4	8	20.603	16.309	4.518	41.430	143.969	33.661	14.422
6	1	2	25.473	23.846	17.789	67.109	161.460	30.000	19.105
7	4	8	31.610	34.855	19.992	86.456	163.710	26.508	18.439
8	6	12	13.043	27.982	19.733	60.759	199.454	22.304	10.000
9	6	11	24.686	24.603	27.485	76.775	195.747	33.955	17.692
10	4	7	14.552	10.899	18.812	44.263	147.312	28.987	8.246
11	8	16	18.125	17.709	10.198	46.032	159.700	34.875	12.083
12	5	9	28.176	17.942	28.607	74.725	202.664	36.066	19.723
13	4	7	28.749	25.613	22.902	77.264	198.871	35.027	20.125
14	7	14	11.655	23.741	24.409	59.805	152.847	30.000	10.296
15	8	15	31.447	16.555	10.672	58.673	215.418	38.254	18.868
16	7	13	10.526	21.949	19.585	52.060	189.217	35.412	12.806
17	5	10	23.461	20.143	13.636	57.240	171.456	33.571	17.205
18	6	11	21.884	6.470	11.765	40.118	69.837	36.471	18.601
Total			361.107	402.207	373.870	1137.184	3007.624	-	

Table 4 Comparison of total time obtained by all algorithms and uncoordinated charging for Case Study-I

EV	Total time without coordination in Min	Total time with a proposed strategy in Min							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	107.3933	119.566	97.357	117.637	99.423	119.566	109.637	119.566	119.566
2	58.08418	82.953	82.953	82.953	82.953	58.084	62.572	58.084	58.084
3	67.48467	58.796	58.796	68.905	68.905	58.796	58.796	58.796	58.796
4	58.03034	49.374	49.374	62.691	62.691	58.030	58.030	58.030	58.030
5	111.766	39.667	41.430	39.667	41.430	39.667	39.667	39.667	41.430
6	79.45396	67.109	67.109	67.109	67.109	67.109	63.134	67.109	67.109
7	70.94265	80.184	70.943	75.666	69.964	80.184	76.515	69.964	86.456
8	65.76365	64.808	64.808	93.435	71.347	60.759	71.936	60.759	60.759
9	83.95032	76.775	70.305	122.381	86.467	76.775	86.378	86.936	76.775
10	55.81435	47.764	44.263	86.683	44.263	47.764	47.764	47.764	44.263
11	55.06661	59.622	55.067	53.290	69.921	46.032	53.290	53.160	46.032
12	133.9968	74.725	78.783	83.366	92.151	74.725	78.783	74.725	74.725
13	113.6569	85.491	93.265	93.673	87.400	85.491	80.911	85.491	77.264
14	168.082	59.805	56.616	102.103	84.267	59.805	99.079	59.805	59.805
15	122.3342	58.673	79.123	82.746	79.123	58.673	58.673	58.673	58.673
16	141.576	52.060	55.466	89.627	64.092	52.060	52.060	52.060	52.060
17	62.7543	57.240	53.524	53.524	66.673	57.240	66.673	57.240	57.240
18	76.69078	40.118	42.667	56.191	42.667	40.118	42.496	42.496	40.118
	1632.841	1174.730	1161.847	1431.645	1280.844	1140.877	1206.395	1150.324	**1137.184**

Table 5 Comparison of $T_w(s_i)$ obtained by all algorithms and uncoordinated charging for CS-I

EV	Queuing time without coordination in Min	Queuing and charging time ($T_w(s_i)$) with proposed strategy in Min							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	48.312	58.951	38.808	61.208	38.808	58.951	53.208	58.951	58.951
2	22.440	23.704	23.704	23.704	23.704	22.440	26.928	22.440	22.440
3	27.397	18.709	18.709	13.720	13.720	18.709	18.709	18.709	18.709
4	13.492	13.312	13.312	18.153	18.153	13.492	13.492	13.492	13.492
5	47.997	14.546	16.309	14.546	16.309	14.546	14.546	14.546	16.309
6	16.112	23.846	23.846	23.846	23.846	23.846	19.872	23.846	23.846
7	13.600	28.583	13.600	18.323	16.630	28.583	23.182	16.630	34.855
8	32.987	22.117	22.117	19.965	28.656	27.982	29.246	27.982	27.982
9	15.306	24.603	18.134	60.607	34.295	24.603	34.207	34.764	24.603
10	12.913	14.400	10.899	35.927	10.899	14.400	14.400	14.400	10.899
11	26.744	22.405	26.744	16.073	32.703	17.709	16.073	24.837	17.709
12	61.719	17.942	22.000	22.400	22.132	17.942	22.000	17.942	17.942
13	33.451	33.840	34.696	35.104	35.749	33.840	29.260	33.840	25.613
14	132.018	23.741	20.552	16.393	12.240	23.741	13.369	23.741	23.741
15	89.516	16.555	27.985	40.628	27.985	16.555	16.555	16.555	16.555
16	111.466	21.949	25.355	19.873	14.278	21.949	21.949	21.949	21.949
17	25.254	20.143	16.427	16.427	29.172	20.143	29.172	20.143	20.143
18	34.137	6.470	9.018	22.542	9.018	6.470	7.128	7.128	6.470
	764.861	405.816	**382.217**	479.440	408.299	405.900	403.295	411.896	402.207

Table 6 Comparison of charging cost obtained by all algorithms and uncoordinated charging for CS-I

EV	Charging cost without coordination in Rs	Charging cost with proposed strategy in Rs							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	236.082	196.627	241.903	207.623	196.627	196.627	207.623	196.6272	196.627
2	204.765	175.032	175.032	175.032	175.032	204.765	182.325	204.765	204.765
3	128.282	110.103	110.103	125.195	125.195	110.103	110.103	110.103	110.103
4	124.467	121.472	121.472	106.829	106.829	124.467	124.467	124.4672	124.467
5	159.218	166.842	143.969	166.842	143.969	166.842	166.842	166.842	143.969
6	176.364	161.460	161.460	161.460	161.460	161.460	181.332	161.46	161.460
7	176.970	189.720	176.970	165.240	179.520	189.720	165.240	179.52	163.710
8	216.691	199.454	199.454	218.538	213.613	199.454	199.454	199.4544	199.454
9	206.869	195.747	195.747	180.176	180.176	195.747	195.747	195.7472	195.747
10	139.392	127.116	147.312	148.104	147.312	127.116	127.116	127.116	147.312
11	171.036	159.700	171.036	173.501	173.501	159.700	173.501	159.6996	159.700
12	237.776	202.664	187.264	197.736	199.584	202.664	187.264	202.664	202.664
13	189.783	171.607	195.129	195.129	171.607	171.607	198.871	171.6066	198.871
14	177.174	152.847	177.174	139.536	159.273	152.847	151.011	152.847	152.847
15	239.629	215.418	230.938	201.139	230.938	215.418	215.418	215.4176	215.418
16	189.217	189.217	163.237	183.335	161.276	189.217	189.217	189.2172	189.217
17	217.704	171.456	185.556	185.556	187.812	171.456	187.812	171.456	171.456
18	76.582	69.837	64.282	69.837	64.282	69.837	64.282	64.2816	69.837
	3268.002	**2976.319**	3048.037	3000.808	2978.005	3009.047	3027.625	2993.292	3007.624

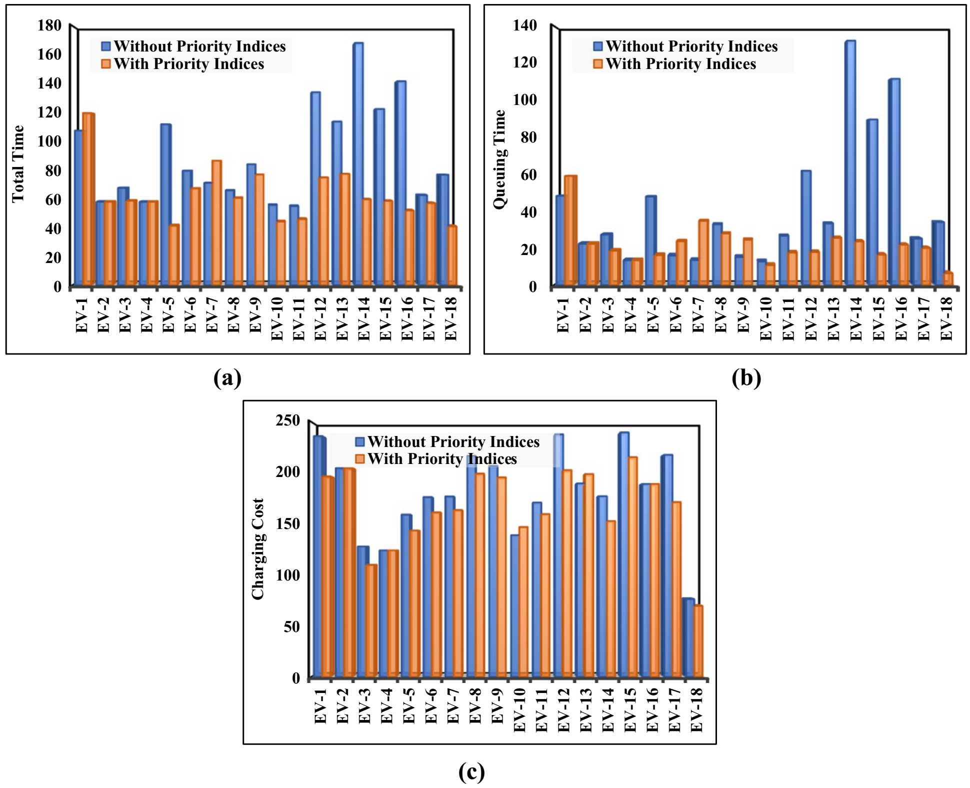

Fig. 5 Effect of priority indices on; (**a**) Total time, (**b**) Queuing time, (**c**) Charging cost for case study-I

Table 7 Priority indices of all EVs for all test case study II

EV	EV-1	EV-2	EV-3	EV-4	EV-5	EV-6	EV-7	EV-8	EV-9	EV-10	EV-11	EV-12
K_d	**1**	**1**	**2**	**1**	**2**	**3**	**1**	**2**	**1**	**1**	**1**	**3**
K_p	1	2	2	1	2	1	2	2	1	2	3	1
K_q	2	3	1	1	1	2	2	1	1	1	2	2
EV	EV-13	EV-14	EV-15	EV-16	EV-17	EV-18	EV-19	EV-20	EV-21	EV-22	EV-23	EV-24
K_d	**1**	**1**	**1**	**1**	**1**	**2**	**2**	**1**	**1**	**1**	**1**	**1**
K_p	2	1	1	1	1	1	2	1	3	2	2	1
K_q	1	1	1	2	1	1	1	1	2	2	2	1

the assigned CS and the distance to be traveled from the assigned CS to its respective destination. In order to validate the performance of the proposed OBMPA in assigning the CS optimally to all EVs, the obtained results in terms of total time, queuing time, and charging cost are compared with the results obtained by other selected algorithms. The results are listed in Tables 4, 5 and 6 respectively for total time, queuing time, and the charging cost. From Table 4, it is observed that the total time obtained by the proposed algorithm is 1137.184 Min, which is less than all other selected algorithms. It is also compared with the total time with an uncoordinated charging strategy as well. It has been seen that a significant difference between uncoordinated charging and the proposed strategy. The performance of the OBMPA is 30.355% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is 3.196%, 2.123%, 20.568%, 11.216%, 0.324%, 5.737%, and 1.142% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively.

Queuing time is the sum of waiting time in queue and time taken by the battery to recharge up to the required SoC level. From Table 5, it is observed that the queuing

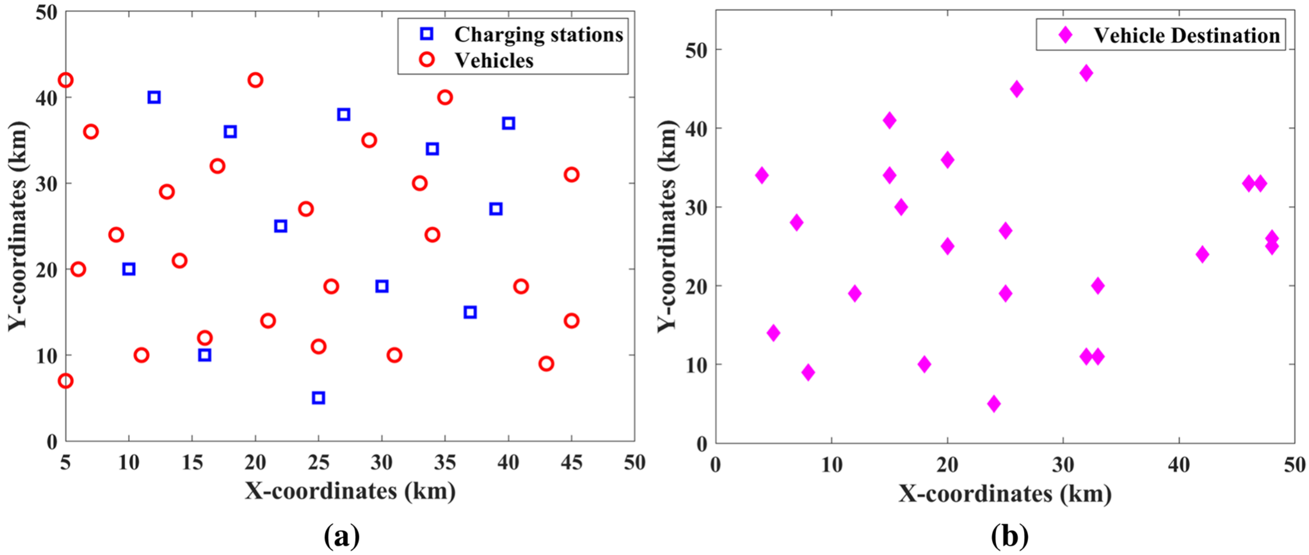

Fig. 6 Position of the CSs and electric vehicles for case study II

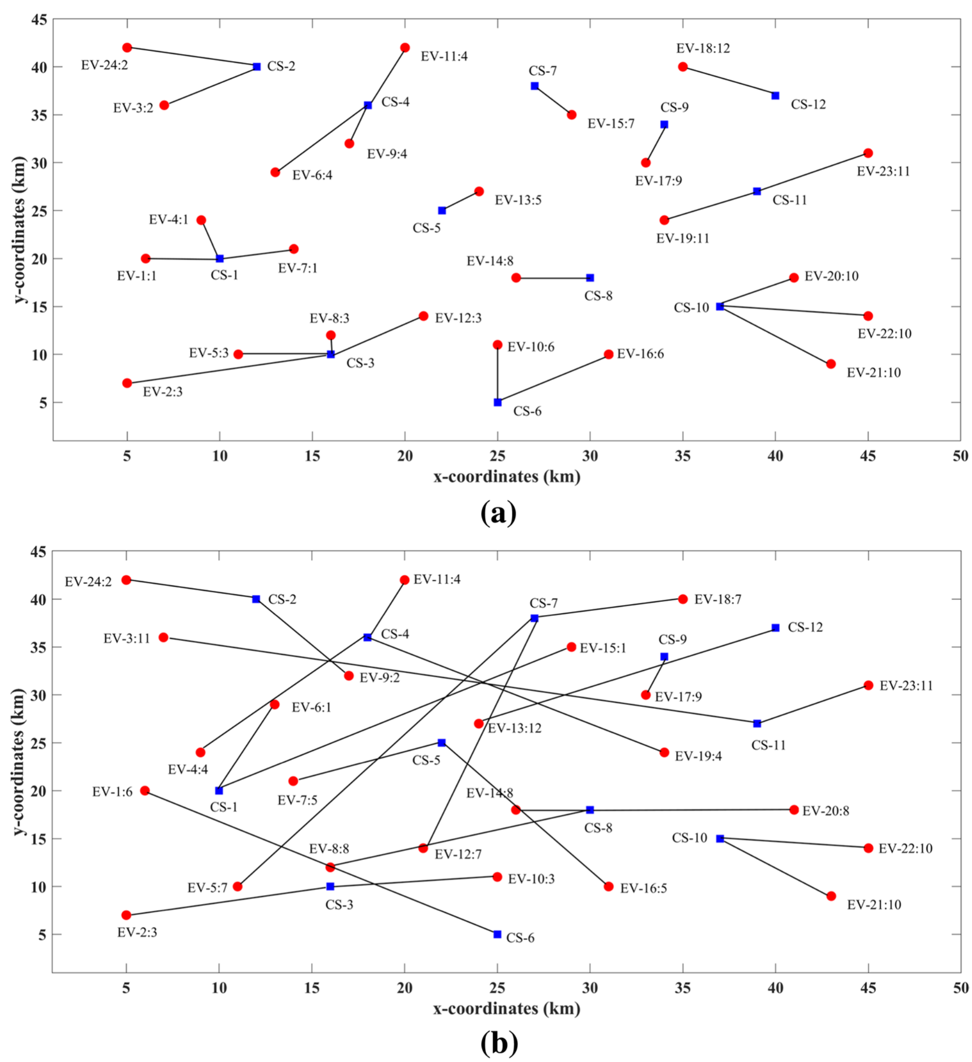

Fig. 7 Charging station allocation for all EVs; (**a**) Without priority indices, (**b**) With priority indices by the OBMPA for CS-II

Table 8 Solution and parameters obtained by the proposed OBMPA for CS-II

EV	CS	Pile	$t_{i\alpha(s_i)}$ in Min	$T_w(s_i)$ in Min	$t_{\alpha(s_i)e_i}$ in Min	Total time in Min	Charging cost in Rs	Range with current SoC in Km	Distance from assigned CS in Km
1	6	12	46.853	12.983	1.935	61.772	133.846	31.543	24.207
2	3	6	12.669	16.369	17.812	46.850	167.048	21.280	11.402
3	11	22	46.384	35.788	14.557	96.729	171.708	34.231	33.242
4	4	7	21.429	14.791	2.857	39.077	131.456	34.133	15.000
5	7	14	41.169	25.849	13.143	80.162	136.136	33.661	32.249
6	1	2	14.595	16.080	11.157	41.833	156.780	28.000	9.487
7	5	9	10.523	20.661	23.559	54.742	149.292	28.052	8.944
8	8	16	19.867	29.154	30.602	79.624	164.629	36.167	15.232
9	2	4	12.305	18.685	13.333	44.324	219.521	52.475	9.434
10	3	6	16.979	34.098	11.518	62.595	180.927	34.865	9.055
11	4	8	9.035	17.608	44.571	71.214	199.731	45.657	6.325
12	7	14	35.341	11.514	10.102	56.957	124.124	34.039	24.739
13	12	24	32.345	20.496	12.730	65.571	199.665	26.518	18.868
14	8	16	5.000	11.860	9.520	26.379	112.892	28.333	4.000
15	1	1	30.259	11.200	4.066	45.525	85.344	31.231	24.207
16	5	10	21.866	24.480	9.763	56.109	155.856	39.186	17.493
17	9	18	3.585	21.786	13.961	39.333	248.297	21.130	4.123
18	7	13	11.780	22.351	27.951	62.082	177.413	27.667	8.246
19	4	8	23.077	33.834	5.547	62.458	184.061	33.129	20.000
20	8	15	16.923	24.908	18.310	60.140	186.238	31.042	11.000
21	10	20	14.142	17.270	29.168	60.580	169.184	37.500	8.485
22	10	19	10.292	22.489	8.537	41.319	185.702	38.667	8.062
23	11	22	10.553	17.785	26.874	55.212	189.006	31.875	7.211
24	2	3	11.495	27.185	3.514	42.193	224.998	30.494	7.280
Total			478.466	509.225	365.089	1352.780	4053.853	-	

and charging time obtained by the proposed algorithm is 402.207 Min, which is less than all algorithms other than MFO with 382.217 Min.

But as far as the total time and charging cost is concerned OBMPA performs better than MFO to achieve overall minimum value among all the other algorithms. It is also compared with the total queuing and charging time with an uncoordinated charging strategy. The performance of the OBMPA is 47.414% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is 0.889%, -53.230%, 16.109%, 1.492%, 0.910%, 0.270%, and 2.352% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively.

From Table 6, it is observed that the charging cost obtained by the proposed algorithm is Rs. 3007.624/-, whereas EO gives Rs. 2976.316 which is less than all other selected algorithms. But while considering priority given to the optimization variables, it can be seen that the OBMPA perform well to reach the user preference with the overall minimal value. It is also compared with the charging cost with an uncoordinated charging strategy. The performance of the OBMPA is 7.967% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is -1.052%, %, 1.326%, -0.227%, -0.995%, 0.047%, 0.661and -0.479% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively. Here negative sign indicates that the minimized charging cost of the respective algorithm is less than OBMPA. This is due to the objective of minimizing overall cost function for this particular data set to obtain the minimal value among all the algorithms.

Total time including driving and waiting time with priority indices is compared with total time without priority indices in the objective function, and comparison is illustrated in Fig. 5a for better understanding. Similarly, the effect of priority indices on queuing time and charging cost is also illustrated in Fig. 5b and c, respectively. It is clear that the

Table 9 Comparison of total time obtained by all algorithms and uncoordinated charging for CS-II

EV	Total time without coordination in Min	Total time with a proposed strategy in Min							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	94.622	61.772	52.087	58.182	61.772	61.772	50.603	65.667	61.772
2	120.236	71.292	46.850	46.850	46.850	46.850	71.292	49.734	46.850
3	97.862	72.837	94.712	117.564	72.837	94.757	121.789	90.155	96.729
4	49.484	39.077	47.560	48.982	47.560	34.026	64.507	39.077	39.077
5	122.552	80.162	85.727	75.194	99.245	85.836	103.731	80.162	80.162
6	129.864	49.873	54.023	41.833	41.833	41.833	49.873	41.833	41.833
7	92.740	62.623	91.050	72.100	67.813	69.458	70.342	48.481	54.742
8	90.413	83.121	86.614	121.002	92.430	79.624	86.088	83.121	79.624
9	56.211	44.324	56.211	69.598	120.965	52.948	44.324	47.232	44.324
10	59.962	56.154	59.962	114.195	59.962	59.962	83.289	71.507	62.595
11	106.642	67.308	71.214	83.677	103.105	77.899	87.977	67.308	71.214
12	135.559	56.957	70.970	90.683	64.482	64.482	73.278	56.957	56.957
13	82.502	65.571	57.953	78.596	71.470	86.182	57.953	73.722	65.571
14	31.562	31.562	60.977	52.656	26.379	26.379	52.656	26.379	26.379
15	51.285	51.468	45.525	61.261	60.540	45.525	51.468	45.525	45.525
16	92.308	70.322	56.109	87.590	70.089	56.109	70.089	72.664	56.109
17	48.876	39.333	39.333	87.610	62.813	39.333	48.876	39.333	39.333
18	85.788	62.082	62.082	74.172	53.248	69.264	73.263	69.264	62.082
19	83.842	62.854	62.458	72.812	51.295	54.591	44.850	65.607	62.458
20	63.030	56.773	91.644	83.105	64.583	63.030	56.773	63.030	60.140
21	111.933	76.644	60.630	60.580	83.448	60.580	79.929	82.948	60.580
22	63.274	34.893	34.893	91.157	52.240	52.240	52.240	34.893	41.319
23	99.761	58.070	58.070	55.212	66.932	68.829	69.960	55.212	55.212
24	66.429	42.193	33.907	33.907	59.929	33.907	42.193	33.907	42.193
	2036.735	1397.263	1480.562	1778.520	1601.820	1425.416	1607.343	1403.718	**1352.780**

desired trade-off between total time and charging cost is obtained using priority indices.

From Table 4, it is clear that the proposed charging strategy reduces the total time spent. From Table 5, it is seen that the sum of queuing time for individual vehicles in the proposed strategy is significantly reduced, from which it is obvious that queue length at most of the CSs is minimized. From Table 6, it is observed that the charging scheduling using the proposed strategy results in cost-saving for electric vehicle users.

4.2 Case Study-2

As discussed earlier, case study-II minimizes charging cost, driving time, queueing time, and electricity pricing for 12 charging stations and 24 electric vehicles. The results obtained by the proposed OBMPA and other algorithms for case study-II are analyzed. The values of K_d, K_p and K_q are listed in Table 7 for optimizing driving time, charging cost and queuing time, respectively. The values of K_{c1} and K_{c2} are tuned to be 4 by considering weightage of driving time, queuing time and charging price towards the cost function. The results obtained by the proposed OBMPA and other algorithms for case study-II are analyzed in this sub-section. The charging station allocation to each EV without and with priority indices is illustrated in Fig. 7 for case study II.

The location of the CSs in the geographical region under consideration and current locations of EVs requesting battery recharging is shown in Fig. 6a, while the destination of vehicles requesting charging is indicated in Fig. 6b.

The charging station allotment is shown in Fig. 7a without priority indices. It is evident from Fig. 7b that each charging station has been allotted with the EVs based on the user priority to choose among driving time, queuing time and charging cost for minimizing the objective function for a better utilization of charging infrastructure.

Table 10 Comparison of $T_w(s_i)$ obtained by all algorithms and uncoordinated charging for CS-II

EV	Queuing time without coordination in Min	Queuing and charging time ($T_w(s_i)$) with proposed strategy in Min							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	54.725	12.983	12.190	18.285	12.983	12.983	12.832	16.878	12.983
2	89.755	17.733	16.369	16.369	16.369	16.369	17.733	18.888	16.369
3	24.235	18.003	33.772	34.083	18.003	33.816	35.083	35.321	35.788
4	16.640	14.791	15.360	17.363	15.360	9.740	15.723	14.791	14.791
5	44.875	25.849	31.415	20.882	44.932	31.524	49.419	25.849	25.849
6	74.476	24.120	28.270	16.080	16.080	16.080	24.120	16.080	16.080
7	36.440	11.478	14.059	11.590	12.571	19.966	12.185	14.400	20.661
8	23.659	27.132	25.717	53.013	24.441	29.154	30.099	27.132	29.154
9	26.298	18.685	26.298	21.516	51.709	27.309	18.685	17.318	18.685
10	26.594	27.658	26.594	28.572	26.594	26.594	36.940	32.077	34.098
11	53.036	18.511	17.608	34.880	31.670	17.189	33.940	18.511	17.608
12	64.219	11.514	20.319	19.344	19.039	19.039	17.911	11.514	11.514
13	31.190	20.496	17.080	33.521	30.597	36.248	17.080	35.112	20.496
14	17.042	17.042	16.224	12.000	11.860	11.860	12.000	11.860	11.860
15	10.583	11.687	11.200	9.956	7.074	11.200	11.687	11.200	11.200
16	45.425	24.480	24.480	24.480	24.480	24.480	24.480	24.480	24.480
17	31.329	21.786	21.786	64.651	34.778	21.786	31.329	21.786	21.786
18	26.529	22.351	22.351	30.982	13.517	23.460	30.073	23.460	22.351
19	30.517	34.230	33.834	41.676	20.160	25.967	16.226	26.192	33.834
20	21.956	17.964	31.569	32.103	25.774	21.956	17.964	21.956	24.908
21	68.622	33.333	15.768	17.270	30.947	17.270	27.429	18.651	17.270
22	44.444	16.063	16.063	15.813	15.813	15.813	15.813	16.063	22.489
23	62.334	20.281	20.281	17.785	29.143	19.817	18.349	17.785	17.785
24	51.420	27.185	18.898	18.898	26.178	18.898	27.185	18.898	27.185
	976.342	**495.357**	517.506	611.114	560.073	508.518	554.284	496.204	509.225

Table 8 shows the obtained solutions by the proposed OBMPA. It is evident from Table 3 that the charging station allocated to each electric vehicle is within its range considering present SoC, and thus, DoD constraints for batteries of all vehicles are satisfied. The boldface in all tables indicates the best result.

From Table 8, it is observed that the total time taken by all 18 EVs is equal to 1352.780 Min., and the total charging cost of all 18 EVs is equal to Rs. 4053.853/-. Table 8 shows the CS station allotment with the respective charging pile number. It also lists the distance traveled by each EV with an existing SoC to the assigned CS and the distance to be traveled from the assigned CS to its respective destination.

In order to validate the performance of the proposed OBMPA in assigning the CS optimally to all EVs, the obtained results in terms of total time, queuing time, and charging cost are compared with the results obtained by other selected algorithms. The results are listed in Tables 9, 10 and 11. From Table 9, it is observed that the total time obtained by the proposed algorithm is 1352.780 Min, which is less than all other selected algorithms. It has been seen that a significant difference between uncoordinated charging and the proposed strategy. The performance of the OBMPA is 33.581% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is 3.184%, 8.631%, 23.938%, 15.547%, 5.096%, 15.838%, and 3.629% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively.

From Table 10, it is observed that the queuing and charging time obtained by the proposed algorithm is 374.439 Min, which is less than other selected algorithms, except GWO and MPA. It is also compared with the total queuing and charging time with an uncoordinated charging strategy. The performance of the OBMPA is

Table 11 Comparison of charging cost obtained by all algorithms and uncoordinated charging for CS-II

EV	Charging cost without coordination in Rs	Charging cost with proposed strategy in Rs							
		EO	MFO	SCA	WOA	GWO	GBO	MPA	OBMPA
1	139.332	133.846	118.853	139.332	133.846	133.846	122.144	145.914	133.846
2	199.500	172.900	167.048	167.048	167.048	167.048	172.900	194.712	167.048
3	200.588	174.333	171.708	170.658	174.333	171.708	161.731	174.333	171.708
4	126.797	131.456	127.130	125.466	127.130	110.490	124.800	131.456	131.456
5	165.750	136.136	136.136	165.750	136.136	136.136	136.136	136.136	136.136
6	190.548	183.794	156.780	156.780	156.780	156.780	183.794	156.780	156.780
7	150.876	129.492	144.936	131.472	123.156	149.292	124.344	151.272	149.292
8	184.838	185.823	185.823	188.288	188.288	164.629	161.178	185.823	164.629
9	233.722	219.521	233.722	226.029	197.628	226.029	219.521	196.444	219.521
10	229.904	216.075	229.904	220.108	229.904	229.904	187.265	192.451	180.927
11	237.632	188.902	199.731	188.902	187.098	185.293	200.934	188.902	199.731
12	151.125	124.124	151.931	151.125	151.125	151.125	147.901	124.124	124.124
13	225.371	199.665	184.122	222.979	184.122	185.916	184.122	195.481	199.665
14	127.426	127.426	126.750	123.708	112.892	112.892	123.708	112.892	112.892
15	84.000	84.448	85.344	88.480	83.104	85.344	84.448	85.344	85.344
16	162.792	149.736	155.856	155.856	160.344	155.856	160.344	153.816	155.856
17	241.348	248.297	248.297	241.348	238.189	248.297	241.348	248.297	248.297
18	176.466	177.413	177.413	186.875	145.715	180.724	157.069	180.724	177.413
19	209.009	184.061	184.061	211.781	211.781	184.061	184.061	207.900	184.061
20	181.298	188.708	155.116	161.538	186.238	181.298	188.708	181.298	186.238
21	199.648	169.184	177.888	169.184	181.696	169.184	205.088	181.696	169.184
22	185.702	157.366	157.366	155.848	165.462	165.462	165.462	157.366	185.702
23	217.906	193.052	193.052	189.006	217.906	193.052	179.758	189.006	189.006
24	224.998	224.998	218.519	218.519	232.655	218.519	224.998	218.519	224.998
	4446.574	4100.757	4087.485	4156.079	4092.575	4062.884	**4041.762**	4090.688	4053.853

47.844% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is -2.800%, 1.600%, 16.673%, 9.079%, -0.139%, 8.129%, and -2.624% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively. Here, the '-' sign indicates that the OBMPA is not better than the other respective algorithm. Even though the queuing time obtained by the OBMPA is slightly greater than GWO and MPA, the total time, including queuing time obtained, is much better than GWO.

From Table 11, it is observed that the charging cost obtained by the proposed algorithm is Rs. 4053.853/-, which is less than all other selected algorithms except GBO. This is due to the objective of minimizing the cost function with both time and cost. In order to achieve overall minimal value, OBMPA choose different set of charging stations than GBO. It is also compared with the charging cost with an uncoordinated charging strategy. The performance of the OBMPA is 8.832% higher than the uncoordinated charging strategy. In addition, the performance of the OBMPA is 1.144%, 0.823%, 2.460%, 0.946%, 0.222%, -0.299%, and 0.900% higher than EO, MFO, SCA, WOA, GWO, GBO, and MPA, respectively. Even though the primary objective is to minimize the total time, the charging cost obtained by the OBMPA is less than other selected algorithms. Therefore, it is proved that the proposed OBMPA can handle case study-II effectively with improved performance compared to all other algorithms.

Total time including driving and waiting time with priority indices is compared with total time without priority indices on case study-II, and comparison is illustrated in Fig. 8a. Similarly, the effect of priority indices on queuing time and charging cost for case study-II is also illustrated in Fig. 8b and c, respectively. It is clear that the desired trade-off between total time and charging cost is obtained using priority indices.

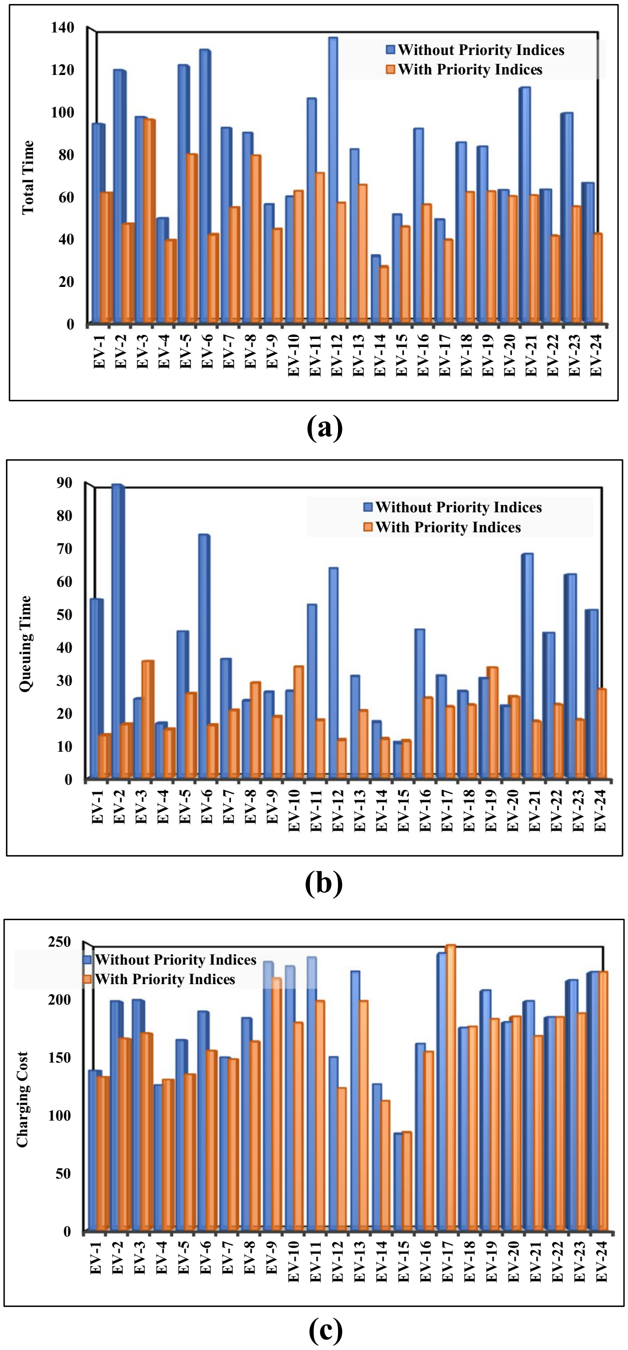

Fig. 8 Effect of priority indices on; (**a**) Total time, (**b**) Queuing time, (**c**) Charging cost for CS-II

From Table 9, it is clear that the proposed charging strategy reduces the total time spent. From Table 10, it is seen that the sum of queuing time for individual vehicles in the proposed strategy is significantly reduced, from which it is obvious that queue length at most of the CSs is minimized. From Table 11, it is observed that the charging scheduling using the proposed strategy results in cost-saving for electric vehicle users.

5 Performance Comparison

The statistical data results, such as the minimum (Min), maximum (Max), Mean, standard deviation (STD), and runtime (RT), can be used to evaluate the effectiveness of the proposed OBMPA. Numerous state-of-the-art algorithms, such as the EO, MFO, SCA, WOA, GWO, GBO, and the basic version of MPA, are also evaluated to assess their effectiveness with the proposed OBMPA. Each algorithm is run 30 times to obtain statistically significant results. According to the previous discussions, the population size and the maximum number of iterations for all algorithms are kept the same. It is also necessary to perform a statistical ranking test known as Friedman's ranking test (FRT) to rank the algorithm based on its performance. Table 12 comprehends a summary of the statistical findings, which includes the FRT values. The boldface in the table indicates the best result.

Interpreting Table 12, it is clear that OBMPA can achieve the lowest (Min) fitness values for all case studies. Compared to other algorithms, the recommended OBMPA can achieve the smallest maximum (Max) value in most cases. The reliability of the algorithm can be determined by examining the STD. When comparing the OBMPA to other algorithms, it can be seen that it achieves the lowest STD values. OBMPA outperforms other algorithms in terms of performance and reproducibility, which implies more reliability and efficiency. The computational complexity of all algorithms can be determined through an RT assessment. Table 12 demonstrated that the developed OBMPA could accomplish the optimization process with much less RT than all other selected algorithms. Based on the generated Min value, all algorithms provide a ranking using FRT with a 95 percent significance level. In all of the case studies, the OBMPA is ranked first among all of the algorithms that were considered.

Figure 9 depicts the convergence curves of all algorithms for all case studies, allowing us to observe the convergence behavior of all algorithms at the same time. It can be seen in Fig. 9 that the convergence rate of OBMPA is significantly higher than that of the other algorithms tested in all case studies. The authors conclude that the proposed OBMPA is a reliable and effective tool for dealing with the charging scheduling optimization problem of EVs.

Table 12 Statistical data and statistical test analysis of all selected algorithms

Case Study	Statistical Data	Min	Max	Mean	STD	RT	FRT
I	EO	8956.720	9206.171	9059.424	130.427	38.599	3.333
	MFO	9181.836	9575.799	9370.072	197.563	72.135	5.667
	SCA	9949.839	10103.567	10008.285	83.221	36.609	8.000
	WOA	9307.245	9825.996	9507.191	279.055	39.641	6.667
	GWO	8900.493	9066.088	8977.906	83.321	78.031	2.667
	GBO	9084.209	9792.889	9429.982	354.651	44.042	5.667
	MPA	8907.080	8989.015	8952.035	43.415	74.182	2.333
	OBMPA	**8887.889**	**8972.058**	**8936.132**	**41.546**	**34.911**	**1.667**
II	EO	14412.653	14683.742	14513.057	148.583	43.984	2.333
	MFO	14819.179	16331.594	15479.609	774.189	88.130	5.667
	SCA	16467.894	16613.431	16562.035	81.643	44.026	8.000
	WOA	15389.187	15708.356	15503.748	177.619	48.094	6.000
	GWO	14422.325	14618.904	14532.869	100.555	94.922	3.000
	GBO	15426.603	15558.501	15472.680	74.391	50.891	6.333
	MPA	14508.566	14731.986	14644.587	119.382	89.896	3.667
	OBMPA	**14103.800**	**14181.484**	**14133.458**	**41.974**	**42.573**	**1.000**

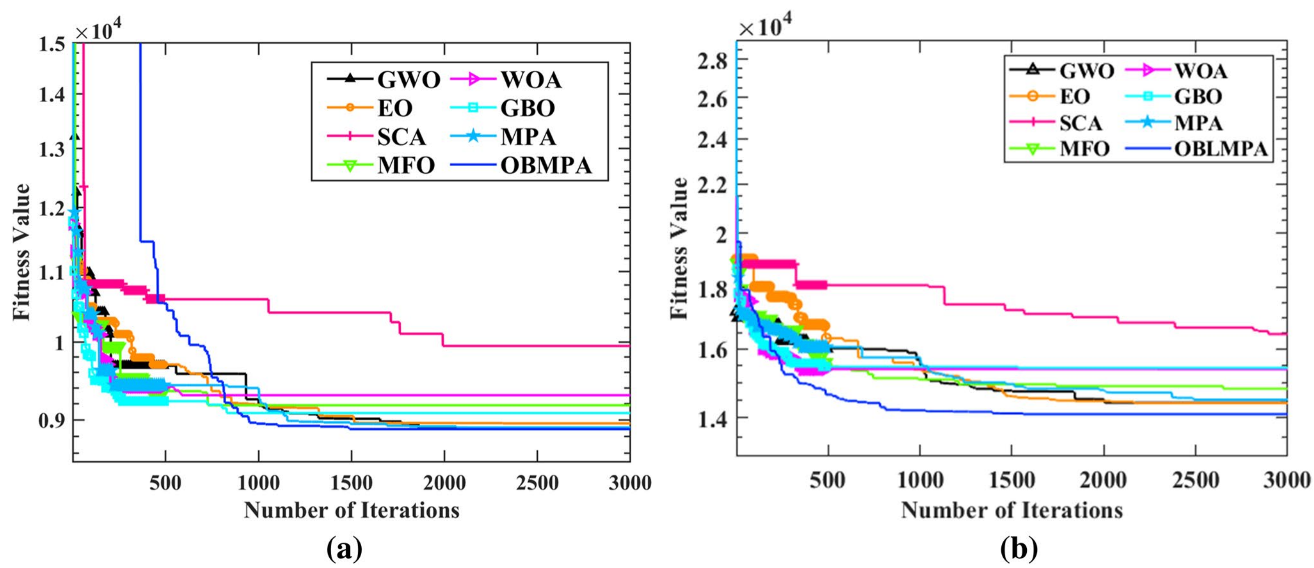

Fig. 9 Convergence curve of all algorithms; (**a**) Case study-I, (**b**) Case study-II

When envisioning statistics, boxplots are a comfortable tool for identifying Min values, Max values, Mean values, and the dispersion of the data, among other qualities. As a result, the boxplots for both the case studies are depicted in Fig. 10. It can be seen and came to a conclusion from Figs. 9 and 10 that the proposed OBMPA is an accurate and stable optimization tool for dealing with the charging scheduling of multiple EVs problems under various constraints.

6 Conclusion

Modeling of the system comprising of electric vehicles and charging stations with multiple charging piles is carried out and presented in this paper. The objective function for optimization is constructed based on the model developed. A charging strategy is proposed using an opposition-based marine predator algorithm (OBMPA) to solve the charging

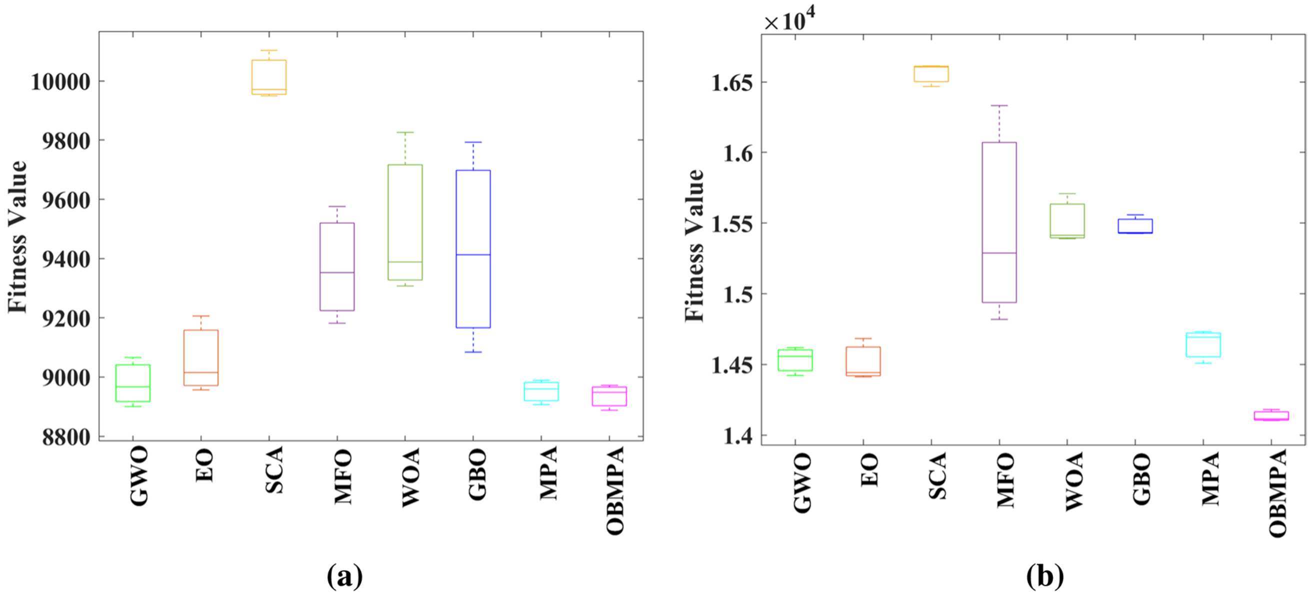

Fig. 10 Boxplot analysis; (**a**) Case study-I, (**b**) Case study-II

pile assignment to electric vehicles. The OBMPA was developed by hybridizing the basic variant of MPA and OBL strategy, which improved the exploration and exploitation phases of the MPA. The proposed strategy was applied to seven different case studies, and the performance was analyzed comprehensively. A performance comparison was also carried out to verify the effectiveness of the proposed strategy and the proposed OBMPA. The results concluded that the proposed strategy and OBMPA significantly reduce the total time spent by electric vehicles traveling to their destination. The strategy also minimizes the cost of recharging. The trade-off between optimization of total time and cost based on the preference given by electric vehicle users during charge requests is also included in the proposed strategy. The assignment of charging stations is such that the maximum permissible limits of DoD are not violated for any electric vehicle battery. Every electric vehicle is allotted a charging station at the optimum distance from the path between the current location and its destination.

In future studies, the proposed scheduling strategy can also be extended to a large number of EVs with more possible constraints. The proposed strategy may also be optimized using multi-objective and many-objective optimization algorithms to get a best-compromised solution. Therefore, the proposed OBMPA may be extended to its multi-objective and many-objective variants in future work. Additionally, the OBMPA may be used for other EV applications, such as CS placement, charging coordination of EVs, power and energy management systems, charging of EV Fleets, energy resource allocation, and so on.

Data Availability Not applicable.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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