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A NOVEL APPROACH FOR LOCATION PLANNING OF FAST-CHARGING STATIONS FOR E-BUSES

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Abstract
This study introduces a robust Electric Bus (EB) charging station planning model, facilitating the transition to a fully EB fleet in smart cities. The Binary Grey Wolf Optimization (BGWO) is implemented to choose suitable positions for fast-charging stations at established bus terminals in the city, considering the construction, operation maintenance, and travel costs of charging stations. The model also contains a novel repair mechanism and an objective function to ensure predefined constraints. The dataset, which includes the Adana province public transportation network of Türkiye, is used to simulate and analyse the model. We compare the proposed model with the recent metaheuristic optimization algorithms: Binary Dragonfly Algorithm (BDA) and Binary Harris Hawk Optimization (BHHO). The results indicate that the proposed approach has promising solutions for fast-charging station locations at a low cost in a reasonable time.
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Key Words: Location Planning, E-Bus, Metaheuristic Algorithms, Fast Charging Station

1. INTRODUCTION

For urban life, the public transportation system plays a crucial role. The use of public buses and their infrastructure cost are cheaper compared to trains and trams. Both electrical and fossil fuel buses are widely preferred for public transportation. The public bus using fossil fuels is one of the significant causes of greenhouse gas emissions. Furthermore, it has environmental impacts, including reliance on fossil fuels, poor energy efficiency, and urban air pollution. Electric drive systems have been considered an alternative to traditional gasoline-powered technology [1]. Many nations and regions have developed policies to promote electric transportation during the past few years [2]. Electric buses (EBs) are suitable for adopting alternative transportation technologies because of their current routes, scheduled operation hours, and common infrastructure [3]. The technical and political city transportation planners want to convert the transportation system from fossil fuels to electricity to overcome these issues.

Unlike public buses that use fossil fuels, EBs use battery systems, power electronics, electrical components, and electric charging stations. Buses with traditional combustion engines may frequently operate continuously for a day without refuelling. However, EBs require charging their battery from the charging station during daily routines. This is one of the biggest issues for EBs and it must be solved more smartly. There are currently three methods of charging: wireless charging [4], plug-in charging [5], and battery swapping [6]. The most promising technology is wireless charging, which provides facilities and enables charging while driving. Although wireless charging is the most sophisticated, its technology and business model are still early and cannot be used in widespread applications. The electric vehicle (EV) charging market is now dominated by plug-in charging, which is more reliable, technologically advanced, and cost-effective than the other two options. Although battery swapping was an early innovation, safety issues brought on by frequent swaps and a lack of battery standards prevent it from becoming widely used [7].

The fast-charging stations for EBs are expensive and require extra power lines. The driver of electric vehicles (EVs) can use the city power grid or fast charging stations. One of the important problems is finding the location of charging stations for EVs. Tang et al. presented key factors affecting the finding of the locations of EV charging stations [8]. EB has to use fast charging stations because of the specific operating characteristics such as route planning and time scheduling table with the difference of private vehicles. The problem has a different mathematical model for EBs. The location of fast charging stations is designed according to EB's capacity and routes, which can reduce fast charging station installation costs and the usage of energy for charging batteries [9].

The main challenge of this problem is correctly determining the charging stations' location in the city, considering the minimisation of the total cost for various sizes and structures of cities. To solve this issue, in this paper, we present a location-planning approach to charging stations for EBs employing a meta-heuristic algorithm. We reduce the total construction, operation, maintenance, and transportation costs to the designated charging stations of the bus terminus. The dataset is created to evaluate the proposed model, which consists of the Adana city public bus transportation network. Meta-heuristic algorithms are modified to handle the problem-specific issues to optimise the total cost, and their results are compared. This study suggests discrete adaptation and novel repair strategies for the Grey Wolf Optimization (GWO), Dragonfly Algorithm (DA), and Harris Hawk Optimization (HHO) algorithms.

2. LITERATURE REVIEW

The facility location problem (FLP) suggests designing an optimal facility location in candidate facility locations according to customers' demand by minimising cost. FLPs have several sub-problems and different applications, such as *p*-median [10], capacitated or un-capacitated facility location problems [11]. Fast-charging station locational planning is considered an application of FLP. This section overviews facility location problems related to electric bus charging stations.

The literature concerning EB operation management, with studies primarily focused on vehicle scheduling, charging strategies, and optimisation of fleet size, has been extending in recent years [12]. Dynamic environmental variables can significantly impact electric buses' charging efficiency, including unexpected traffic congestion, changing travel demand, and even various weather conditions. Building charging infrastructure at current bus terminals is essential, given the growing popularity of EBs [13]. Kunith et al. performed a study on fast-charging infrastructure planning and locating charging stations for BEBs in public transportation [14]. They designed a mixed integer linear optimisation approach to locate charging stations along a bus route. Wu et al. considered the distribution of charging stations and optimised bus operating networks for this problem [15]. The objectives of their approach were to decrease the overall construction expenses for fast chargers, as well as the costs associated with their maintenance and operation, travel to the chargers, and power loss.

In another study, the authors developed a MILP model to help decision makers identify a heterogeneous bus fleet when all chargers were replaced for EBs [16]. Zeng et al. [17] proposed in their study a bus replacement strategy in which buses with low batteries were replaced with spare buses, and passengers were transferred to buses with fully charged batteries. Guschinsky et al. studied the combined decisions regarding the equipment and charging schedule for EBs formulated as a MILP problem [18]. Liu et al. presented a study considering the total charge station construction cost using MIP Model and proposed an improved PSO to simulate electric vehicles by finding the optimum location of charging stations [19].

The research on the literature discussed above shows a few essential studies on facility locating charging station problems (FLCSP). DA, GWO, and HHO algorithms have become popular in recent years and have been preferred by researchers because they are robust. Furthermore, BDA, and BHHO have not been investigated in depth to solve locating charging stations problems in the related literature. In this study, binary versions of GWO, DA, and HHO are adapted using a repair method to choose charging stations' locations.

3. PROBLEM DESCRIPTION

This section presents the mathematical notations and explanations of the problem. In the proposed mathematical approach, the mathematical models of FLCSP in [15] are adopted to minimise total cost and perform other meta-heuristic algorithms. Table I shows the mathematical notation of variables and parameters used in this study.

Table I: Nomenclature.

Abbreviation	Description	Abbreviation	Description
FLCSP	Facility locating charging station problem	$var1$	The operating state of EB
EB	Electric Bus	$var2$	The charging state of EB
SOC	State of Charge	$E_{i,c}$	Energy consumption from bus terminus *i* to charging station *c*, kWh
GWO	Grey wolf optimizer	$SOC1$	State of charge at departure
HHO	Harris hawk optimization	$SOC2$	State of charge at arrival
DA	Dragonfly algorithm	TD	Dwelling time of e-buses, minute
Parameters		TC	Charging time of e-buses, minute
η_b	Assuming scaling factor, %	$T_{i,c}$	Driving time from terminus *i* to charging station *c*, minute
g_t	Electricity price of charging, $/kWh	NS_c	Number of charging spots to be built for the fast-charging station *c*
r_0	Discount rate	NT_c	Number of transformers in the charging station *c*
γ	Operating life of the charging	NB_j	Number of EBs of route *j*
ω_c	Construction cost of charging station *c*	NJ_i	Number of bus routes operated by charging demand point *I*
p_1	Unit price of the charging facility, $	NC	Number of charging stations
p_2	Unit price of the transformer, $	i	Terminus node, $i \in \{1, ..., I\}$
C_{bat}	Battery capacity of EB, kWh	j	Route number, $j \in \{1, ..., J\}$
F	Objective function	b	The EBs index, where $b = 1, 2, \ldots, NB_j$
C_{1c}	Equipment and installation cost of charging station *c*, $	t	Time period (tour number on the route for a bus), $t \in \{1, ..., T\}$
C_{2c}	Operation and maintenance cost of charging station *c*, $	$\vec{x_i}$	The set of bus terminus
C_{3c}	Travel cost of EB to charging station *c*, $	c	The fast-charging station index, where $c = 1, 2, \ldots, NC$

3.1 Public bus transportation system

A Public Bus Transportation System (PBTS) can be presented as a complex graph. PBTS contains several routes, a transportation network, bus terminuses, bus stops, and the scheduling of the bus routes. Fig. 1 shows a sample EB transportation model. The thick straight blue lines show city roads. Routes is a set of route and $R = [r_1, r_2, r_3, r_4]$. Each bus uses a route to serve its passengers using a timetable. A route can be used by more than a bus according to a timetable. White circles show bus stops. Blue circles (x_i) present the initial or final terminus for buses. The dotted coloured line with arrows (r_i) indicates a route. r_1 serves between x_1 and x_2.

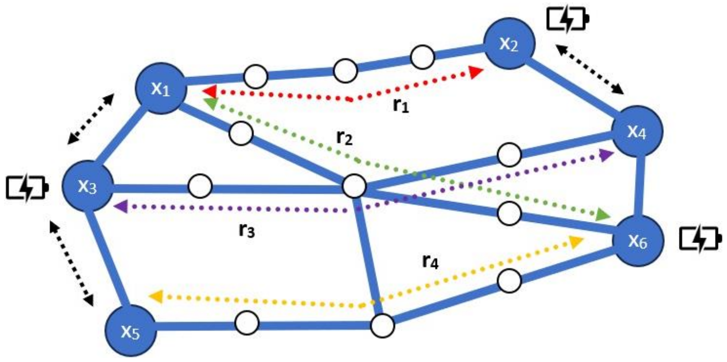

Figure 1: A sample EB transportation system.

The EBs may only be recharged around the terminus during the waiting period for the next departure after the previous tour on their routes. The expenditure will be too much if charging stations are provided at each bus terminus. Having all the charging stations at every bus terminal is quite costly. Thus, the location of the charging station can be determined. Each terminus with a battery is selected to construct charging stations (x_2, x_3, and x_6). EBs must choose the nearest terminus with a charging station for the routes without a charging station. The dotted black line with arrows charges the bus battery when the bus needs energy. For example, EBs using r_2 route on x_1 terminus use x_3 to charge their batteries when they are low.

The main flow of the EB's operation process is given in Fig. 2. In the first step, according to its schedule plan, the bus is ready to leave the first departure stop, and its battery is full. The *SOC* value of the e-bus is set to 1. The variable $var1_{i,j,b,t}$ is equal to 1 because the bus is ready to depart. In the second step, the position of the e-bus is the last terminal. In this step $var1_{i,j,b,t}$ is set to 0 since the position of the e-bus is the destination stop. In the third step, it is calculated whether the state of the e-bus's battery is enough to go to the charging station or not. If the e-bus requires charging, the $var2_{i,j,b,t}$ variable is to be 1 otherwise 0 and the e-bus waits for the next trip. In step 4, the charging time is calculated if the bus goes to charge. In step 5, the e-bus runs for the new trip. In this step, the *SOC* value is calculated. Steps 2 to 5 are repeated for the first and last terminals of all buses.

The equations in the figure are explained in detail in Section 3.2.

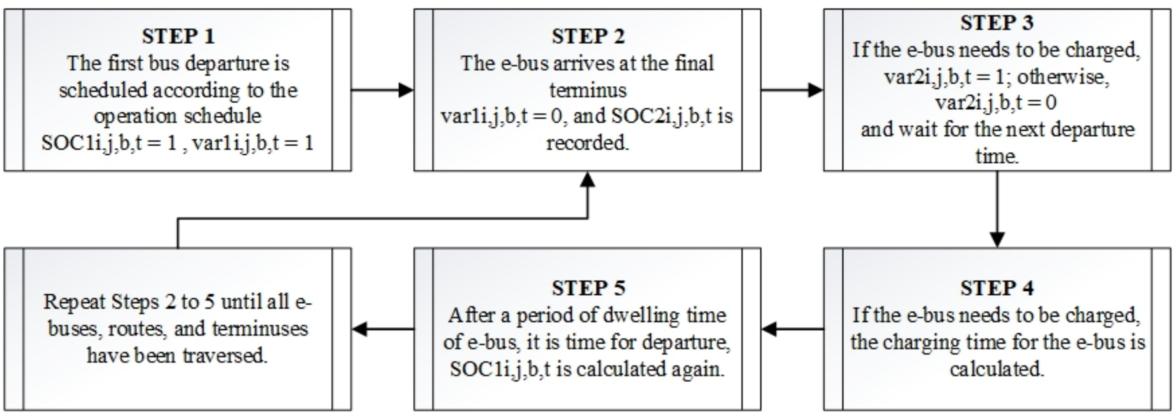

Figure 2: Steps of the simulation model.

3.2 Mathematical model for electric buses

Decision makers for this problem aim to minimize the charging station's overall cost, including equipment and installation costs, operation and maintenance costs, and travel costs of EB to charging stations. We use the following decision variables, parameters, and notations.

$$x_i = \begin{cases} 1 & \text{if the terminus is selected for charging station} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where x_i shows whether i^{th} terminus is selected and x_i are either 1 or 0.

$$var1_{i,j,b,t} = \begin{cases} 1 & \text{EB is ready for departure} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$var2_{i,j,b,t} = \begin{cases} 1 & \text{EB is needs to be charged} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The operating state variable ($var1_{i,j,b,t}$) in Eq. (2) controls whether the EB is at the departure or the final stop. The charging state variable ($var2_{i,j,b,t}$) in Eq. (3) controls whether the EB needs charging. The fitness function of EB charging station planning given by Eq. (4) is to minimize the overall cost of the charging station.

$$Minimize\ F = \sum_{c=1}^{NC} (C_{1c} + C_{2c} + C_{3c}) \quad (4)$$

where NC presents number of charging stations, C_{1c} means equipment and installation cost of charging station *c*, C_{2c} shows operation and maintenance cost of charging station *c*, C_{3c} define travel cost of EB to charging station *c*; subject to:

$$d_{i,c} \leq L \quad \forall_i, \forall_c \quad (5)$$

$$TC_{i,j,b,t} \leq TD_{i,j,b,t} - 2T_{i,c} \quad (6)$$

where $d_{i,c}$ shows the distance between the charging demand terminus i and the fast-charging station *c*, L presents service distance constraint of charging station, $TC_{i,j,b,t}$ means charging time of e-bus *b* in route *j* operated by terminus *i* at the time of its t^{th} dwell, $TD_{i,j,b,t}$ represents dwelling time of e-bus *b* in route *j* operated by terminus *i* at the time of its t^{th} dwell, and $T_{i,c}$ means driving time from terminus *i* to charging station *c*.

Eq. (5) shows that to satisfy the charging dependability, the distance from the current station (*i*) to the charging station. Eq. (6) shows that not exceeding the spacing interval, the charging time needs to meet the constraint of the charging time of e-buses. The equipment and installation cost of the charging station is calculated in Eq. (7).

$$C_{1c} = (NS_c.p_1 + NT_c.p_2 + \omega_c)\frac{r_0.(1+r_0)^\gamma}{(1+r_0)^\gamma - 1} \quad (7)$$

where γ represents the charging station's operating life, r_0 is discount rate, NS_c is the charging facilities count at the charging station *c*, NT_c is the transformers count in the charging station *c*, p_1 is the charging facility's unit price, p_2 is the transformer's unit price, ω_c is the charging station's construction cost *c*. Eq. (8) shows the cost of the charging station's annual maintenance and operation.

$$C_{2c} = C_{1c}\eta_b \quad (8)$$

where η_b represents assuming scaling factor. Travel cost to the charging station is calculated in Eq. (9).

$$C_{3c} = 365 \sum_{c=1}^{NC} \sum_{i=1}^{NJ_i} 2g_t E_{i,c} n_{c,i} \quad (9)$$

where g_t denotes charging electricity price and $n_{c,i}$ represents charging times count of terminus *i* of charging station *c*.

4. SOLUTION ALGORITHMS

In this section, the binary implementation of grey wolf optimization (BGWO) is comprehensively explained to solve FLCSP. Binary Dragonfly Algorithm (BDA) and Binary Harris Hawk optimization (BHHO) are briefly given in this section.

4.1 Binary solution representation for FLCSP

The mostly meta-heuristic techniques are first tested using well-known problems such as CEC-Function [20], a set of 0–1 multidimensional knapsack problem (MKP) benchmark instances [21]. These methods and solution models must be implemented to find a good solution in different search spaces and constraints. In this study, a problem-specific binary form is implemented for FLCSP using an S-shaped transfer function for binary search space.

A solution structure has *I* binary bits, and *I* is the number of the terminus. Therefore, *D* is *I* for *D*-dimensional search space. Eq. (1) computes the position of the x_i. Whether a terminus is chosen for the charging station, the corresponding position is 1 or 0. A solution space has feasible and unfeasible solutions. If the solution is unfeasible, namely, if the service diameter (L) is more than 3 kilometres for the dataset, the solution is repaired. Fig. 3 presents the repair algorithm. These algorithms control a solution ensuring Eq. (5). If the uncovered terminus exists, the unused terminus is selected for a charging station to support that terminus.

```
Algorithm 1: The repair algorithm
Input Parameters: solution (sol);
Result: new solution (nSol)
TerminusList = NotCoveredTerminus(Sol);
while TerminusList ≠ Φ do
    selTerminus ← RandomSelectTerminus(TerminusList);
    sol(selTerminus) ← 1;
    TerminusList = NotCoveredTerminus(Sol);
end
```

Figure 3: The repair algorithm.

4.2 Grey wolf optimizer

The Grey Wolf Optimizer (GWO), one of the most popular swarm intelligence approaches, imitates the hunting and searching for prey behaviours and movements of grey wolves [22]. GWO is a population-based search technique and divides the population into two parts: three swarm leaders (alpha, beta, and delta) and omega wolves. The alpha wolf is the pack's leader and dominates other population members. While the beta wolf acts as the second in a swarm, the delta wolf is the third leader. Omega wolves obey and follow the leader's commands. The three solutions with the swarm best fitness values are α, β, and δ. The other solutions are called ω. To solve difficulties with continuous values, GWO was initially presented in 2014 [22]. Binary GWO (BGWO) is introduced using S-shape and V-shape transfer functions by Emary et al. [23]. We modified BGWO to solve FLCSP. The original BGWO is detailed in [23]. In this section, BGWO is explained. The pseudo-code of BGWO is presented in Fig. 4.

The behaviours of grey wolves are mathematically modelled using three methods: surrounding, hunting, and attacking for prey. The following Eqs. (10) to (13) are used to simulate encircling prey in hunting prey process.

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \quad (10)$$

where t indicates the number of iterations, $\vec{A}$ and $\vec{C}$ are coefficient values and calculated using Eq. (12), respectively. $\vec{X}_p$ is the prey's position while the wolf vector's position is shown as $\vec{X}$.

```
Algorithm 2: The pseudo-code of modified BGWO for locating charging station
Result: The best solution
Initialization phase:
 Randomly Initialize solutions in the population of grey wolves;
foreach X_i ∈ the population of grey wolves do
 | Evaluate X_i using f by Eq. (4);
end
Initialize a, A and C parameters;
X_α ← the position of the best wolf;
X_β ← the position of the second best wolf;
X_σ ← the position of the third best wolf;
iter ← 0;
while iter < Iter_max do
  foreach X_i ∈ the population of grey wolves do
   | Update the position of the current search agent;
   | Compute X_1,X_2,X_3 using Eq.(16),(17) and (18);
   | Generate X_i^new by applying Eq.(22));
   | Repair X_i wolf considering the constraints;
  end
  Evaluate the fitness of all grey wolves;
  Update the position of alpha, beta, and delta;
  Update a, A and C parameters;
  iter ++;
end
```

Figure 4: The pseudo-code of modified BGWO for locating charging station.

$\vec{D}$ is calculated using Eq. (11).

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \tag{11}$$

$$\vec{A} = 2a.\vec{r}_1 - a\ ,\ \vec{C} = 2.\vec{r}_2 \tag{12}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors ranging between 0 and 1. $\vec{a}$ elements are generated using Eq. (13) and decrease linearly from 2 to 0 across iterations.

$$\vec{a} = 2 - t \cdot \frac{2}{maxIt} \tag{13}$$

where $maxIt$ shows the maximum number of iterations. Four wolves are in a wolf pack's leadership hierarchy: α, β, δ, and ω. α, β, and δ represent the positions of the three best search agents, and the positions of each wolf represent a solution for the problem. In every iteration, the new positions of the wolves are updated using Eq. (14).

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{14}$$

where Eq. (15), the positions of all wolves are updated by the positions α, β, δ. $\vec{A}_1$, $\vec{A}_2$, and $\vec{A}_3$ are calculated using Eq. (12). Eq. (16) calculate $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$, respectively.

$$\vec{X}_1 = |\vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha|, \vec{X}_2 = |\vec{X}_\beta - \vec{A}_2.\vec{D}_\beta|, \vec{X}_3 = |\vec{X}_\delta - \vec{A}_3.\vec{D}_\delta| \tag{15}$$

$$\vec{D}_\alpha = |\vec{C_1}.\vec{X}_\alpha - \vec{X}|,\ \vec{D}_\beta = |\vec{C_2}.\vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C_3}.\vec{X}_\delta - \vec{X}| \tag{16}$$

where Eq. (12) is adapted to calculate $\vec{C_1}$, $\vec{C_2}$, and $\vec{C_3}$.

This paper proposes a BGWO-based approach to solve the locating charging station problem. In the binary version of the algorithm, the S-shaped transfer function is implemented, as in Eq. (17). Eq. (17) shows the S-shaped transfer function for binary solution space.

$$X^d(t+1) = \begin{cases} 1 & \text{if } S(\frac{X_1^d + X_2^d + X_3^d}{3} \geq r_7) \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

where r_7 is a random vector ranging between 0 and 1, *d* is the size of search space, and *S* represents the Sigmoid function,

$$S(x) = \frac{1}{1 + \exp(-10(x - 0.5))} \tag{18}$$

4.3 Dragonfly algorithm

Another metaheuristic algorithm based on swarms called the Dragonfly Algorithm (DA) was proposed by Mirjalili [24]. The DA imitates the flight and hunting strategies of dragonflies. The dragonflies use a hunting strategy known as a static swarm (feeding), in which they fly in small groups over a restricted region in search of food sources. Dynamic swarm (migratory) is the name of the migration mechanism. During this phase, the swarm migrates due to the dragonflies flying far away in one direction. The binary version of the algorithm (BDA) was proposed by Mirjalili [24]. In this study, BDA is performed to solve the problem.

4.4 Harris hawk optimization

Heidari et al. presented the metaheuristic method called Harris Hawk Optimization (HHO) [25]. HHO imitates Harris hawk principles to investigate the prey, surprise pounce, and many assault techniques used in nature. The best solution is called prey in HHO, whereas hawks symbolise the candidate solutions. Thanks to their sharp eyesight, Harris hawks attempt to trace their target before performing a surprise leap to capture it. These steps construct the exploitation and exploration stages of HHO. The escape energy of prey is used to modify the exploration behaviour and causes the transition from exploration to exploitation. The binary version of HHO (BHHO) was proposed by Too et al. [26]. In this study, BHHO is adapted to solve the problem.

5. EXPERIMENTAL RESULTS

This section presents experimental results. The performance of the proposed mathematical solutions using the binary versions of GWO, DA, and HHO are investigated. The real-world dataset is used to evaluate the performance of models. Ten independent runs are performed for the proposed algorithms. All experiments are executed on a desktop computer with 8 GB RAM, an Intel i5 CPU 3.0 GHz, and Windows 11 Pro OS. For all algorithms, the search individuals were determined as 20, each run was 100 iterations, and each algorithm was run 10 times independently. The algorithms have no special parameters.

Some experiment parameters were determined as in the previous works. These parameters are discount rate (%), $r_0 = 5$ [27], operating life of the charging station (year), $\gamma = 20$ [28], the charging facility unit price (\$), $p_1 = 777000$ [29], the transformer unit price (\$), $p_2 = 40000$ [30], charging station construction cost c (\$), $\omega_c = 63400$ [31], assuming scaling factor (%), $\eta_b = 0.5$, and electricity price of charging (\$/kWh), $g_t = 0.9822$ [32]. In this study, the battery capacity of e-buses (C_{bat}) is 120 kWh. The average speed of EBs is assumed to be 25 km/h. In addition, the power of the chargers used in the charging stations is 180 kW. $var1_{i,j,b,t}$, $var2_{i,j,b,t}$, $SOC1_{i,j,b,t}$, and $SOC2_{i,j,b,t}$ are the operating state, the charging state, the state of charge when the EB is departing, and the state of charge when the EB is arriving at bus b in route j of terminus i at the time of its t^{th} departure or arrival, respectively. Fig. 5 shows the variation of SOC in the operation for e-bus 1. It is assumed that the bus with 120 kWh batteries on route 1 starts at 6 am for the first trip and stops at 6 pm for the last trip.

The e-bus runs between the terminus with ID 2 and the terminus with ID 4 throughout the day. Assuming that the SOC initial value of the e-bus is 1 for the first trip, the state of the batteries is full. The SOC value decreases throughout the trip until recharging is required. There are important factors for the bus's battery consumption, such as route length, number of stops on the route, and weather conditions.

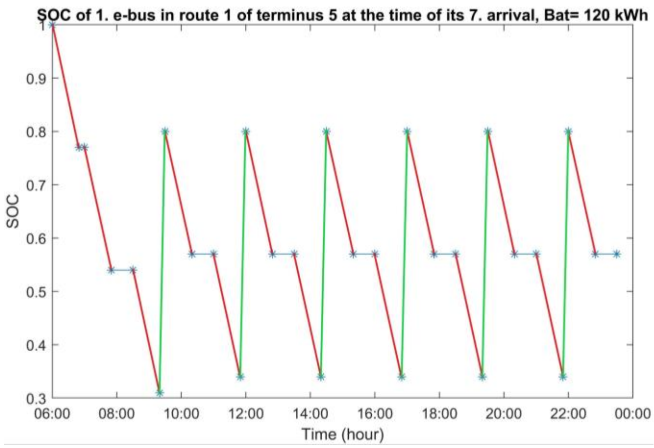

Figure 5: *SOC* of EBs in the operation.

Red lines show the battery consumption; green lines show the charging duration and horizontal blue lines show the waiting time for EBs at the terminus. If the *SOC* value of the e-bus decreases to 0.2 or less, the e-bus needs to be charged. It is checked that it has a certain amount of charge before it can complete the next trip. While the e-bus charges, the SOC value is limited to 0.9 to prevent overcharging. Thus, Fig. 5 shows that the e-buses on their route can run without the related battery charge problem.

5.1 Datasets

The dataset was created based on the urban transportation network of Adana province in Türkiye. Bus timetable, routes, and terminuses data were obtained from the Adana Metropolitan Municipality transportation web page in 2022. The dataset consists of 46 routes and 187 buses covering the places close to the city centre. The locations of the terminals of the dataset are shown in Fig. 6.

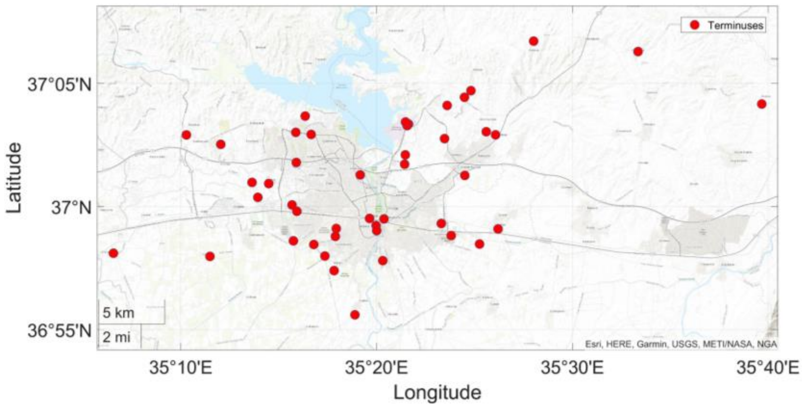

Figure 6: Locations of terminuses of the dataset.

The red points in Fig. 6 represent candidate charging stations in the city. There are 45 candidate charging stations.

5.2 Numerical results

The distance constraint from any terminus to another terminus having charging stations is 3 kilometres. The distance was calculated based on the Haversine distance. Table II presents the average, minimum, maximum, and standard deviation of fitness values and the execution times for 10 runs. As seen from the table, BGWO obtained the best average fitness value. Also, BGWO achieved the best standard deviation value, which shows the algorithm's robustness.

Moreover, the results show that BGWO has the best execution time. BHHO attained the worst average running time, getting 17.977 seconds. BDA and BHHO algorithms present close results for the average fitness value. BGWO attained the best standard deviation values, showing these algorithms achieved similar results for every run.

Table II: The numerical results of fitness values and execution times.

Method	Fitness values				Execution times (sec.)			
	Avg.	Min.	Max.	Std. dev.	Avg.	Min.	Max.	Std. dev.
BDA	7,608,227.12	7,227,978.99	7,988,492.68	253,325.80	9.661	9.393	**10.314**	**0.282**
BGWO	**7,151,594.15**	**6,847,200.00**	**7,608,000.00**	**240,547.04**	**9.462**	**8.970**	10.788	0.694
BHHO	7,760,733.96	7,608,000.00	8,368,800.00	265,684.30	17.977	17.560	18.499	0.299

Table III presents sub-cost values and the selected charging stations for the best solutions. BGWO has the minimum value of C3 (Travel cost to charging station).

Table III: The Sub-Cost values for the best solutions.

Method	Total cost	C1	C2	C3
BDA	7,227,978.99	4,818,400	2,409,200	378.99
BGWO	**6,847,200**	**4,564,800**	**2,282,400**	**~0**
BHHO	7,608,000	5,072,000	2,536,000	**~0**

Fig. 7 shows the average convergence rates of 10 runs. The convergence performance of BGWO is faster than the other methods.

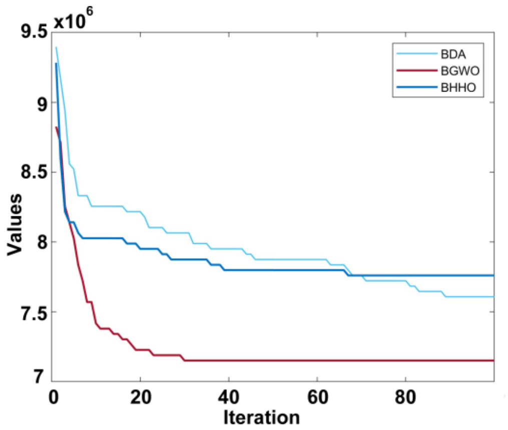

Figure 7: Convergence curves of the proposed algorithms.

6. CONCLUSION

This study presents a comprehensive model for planning e-bus charging stations in smart cities, facilitating the transition to a fully electric bus fleet. This model employs a metaheuristic method to generate robust solutions for the suitable location of fast-charging stations at established bus stations in the city. The proposed model also has a novel repair mechanism and an objective function to satisfy the predefined constraints. We compare the proposed model with the latest metaheuristic optimisation algorithms: BDA, BGWO, and BHHO. The dataset is used to evaluate and compare the models' performance. The numerical results show that BGWO achieves promising results. The proposed model presents better locations for fast-charging stations with low costs and reasonable time than others. The objective function provides lower charging costs and the total cost of fast-charging stations. This model can be applied to any location facility problem to modify the objective and repair functions.

The model's best solution has approximately zero value for travel cost to the charging station (C3), an operating cost in the dataset. In contrast to the equipment and installation costs (C1), this value affects the time and operating costs, especially gas emissions. In the future, the proposed models can be extended to consider the positions of the power distribution network and the self-charging EB models. Multi-objective optimisation algorithms can be implemented to optimise conflicting objectives for charging station location planning.

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