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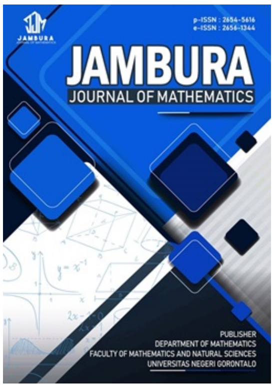

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Research Article

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Optimized Approach to Electric Vehicle Routing Problem with Time Windows using Grasshopper Optimization Algorithm

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ABSTRACT. *The Electric Vehicle Routing Problem with Time Windows (EVRPTW) is a complex logistics issue that involves optimizing delivery routes for electric vehicles while adhering to strict time limits, managing limited battery capacity, and addressing recharging needs. In this research, we introduce an optimized method to tackle the EVRPTW using the Grasshopper Optimization Algorithm (GOA), a metaheuristic inspired by the swarming behavior of grasshoppers. We utilize the Solomon dataset, a recognized benchmark in logistics and vehicle routing, to assess the effectiveness of our proposed algorithm. Our focus is on minimizing the total distance traveled while ensuring timely deliveries and effectively managing battery logistics and recharging. Comparative analysis indicates that the GOA surpasses traditional methods in route efficiency, reducing travel distances, and enhancing logistical operations. This study highlights the potential of GOA as a valuable tool for overcoming the challenges associated with electric vehicle logistics, paving the way for more sustainable and efficient transportation systems.*

1. Introduction

Indonesia's government has enacted Presidential Regulation Number 55 of 2019 to accelerate the conversion of battery electric vehicles (BEVs) for use on roads, including electric cars [1, 2]. This move is aimed at reducing pollution levels and addressing social and transportation issues [3, 4]. The transportation sector is transitioning to electric energy to reduce greenhouse gas emissions and address urban health issues [5]. EVs are energy-efficient and can benefit public transit, food delivery, courier, and distribution businesses [6]. However, adoption remains limited due to challenges like restricted driving range, high costs, lengthy charging times, and infrastructure scarcity [7, 8]. Electric vehicles are gaining popularity as a sustainable alternative to fossil fuels due to their ability to decrease greenhouse gas emissions and air pollution [9].

The growing use of electric cars in transportation and logistics has sparked interest in the Electric Vehicle Routing Problem (EVRP) in research and industrial applications [10]. EVRP is an extension of the basic VRP that includes considerations of charging requirements [11]. The EVRP is an optimization problem that uses a variety of optimization techniques and algorithms to discover the best route plan for electric vehicles while minimizing expenses, adhering to operating constraints, and taking charging requirements [8]. Metaheuristic algorithms are precise optimization techniques used to find nearoptimal solutions [12] in complex problems like scheduling, machine learning, supply chain management, engineering, and routing [13]. It is evident that these algorithms can provide high-quality solutions for optimization problem. Additionally, metaheuristic algorithms are effective in solving of complex optimization problems, including the EVRP [14]. Some commonly used methods include Genetic Algorithm (GA), Variable Neighborhood Search (VNS), and Ant Colony Optimization (ACO) [15].

In this paper, we present the Grasshopper Optimization Algorithm (GOA) is an algorithm inspired by the behaviour of grasshoppers swarms [16] to solve optimization problems. In the first step of initialisation with GOA, grasshoppers move widely, which helps them to search globally for food, and move locally in the last stage of optimisation, which allows them to exploit the search space [17]. This algorithm is able to solve optimisation problems better than some other algorithms such as Bat Algorithm, Genetic Algorithm, Flower Pollination Algorithm, Firefly Algorithm, and Particle Swarm Optimisation Algorithm. The results obtained using GOA have better solutions with a high level of accuracy, and are easy to implement [16].

The Electric Vehicle Routing Problem with Time Windows (EVRPTW) incorporates EV routing and charging at available stations, influenced by the vehicle's battery level upon arrival. The GOA designed to efficiently navigate the complexities of EVRPTW by leveraging its unique optimization capabilities. The paper uses Solomon's benchmark problems to test and assess the effectiveness of the GOA. The algorithm's effectiveness and efficiency are demonstrated, showing competitive solutions within reasonable computational times. The findings have practical implications for logistics companies and urban transportation planning. The study concludes with suggestions for future research to refine and adapt the GOA to address more complex EVRPTW problems.

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2. Model

2.1. Model Construction

The Electric Vehicle Routing Problem with Time Windows (EVRPTW) is a complex optimization challenge that integrates logistics, energy management, and time-sensitive delivery operations. With the increasing adoption of electric vehicles (EVs), there is a need to optimize routes to minimize travel distances and ensure timely deliveries, considering battery capacities and recharging station availability. The problem is typically modeled using graph theory, with the objective of identifying the most efficient routes for a fleet of EVs to serve a set of customers within designated time windows. The mathematical model of the EVRPTW is formulated using a directed graph $G = (V, E)$, where V represents the set of vertices and E represents the set of edges connecting these vertices. The model provides a framework for solving the EVRPTW, considering factors such as travel distances, service times, and battery limitations. The definitions and notations utilized in the model are summarized in Table 1 and the EVRPTW model's settings and notations are described as follows:

Table 1. Parameter and decisions variable for EVRP

Notation	Description
Sets	
N	Set of customers, $\{1, 2, \ldots, n\}$, $i,\ j \in N$
SM	Set of charging stations, $\{1,\ 2, \ldots, m\}$, $l \in S$
	Set of recharging stations
V	Set of customers, charging stations, and depot, $V = N \cup S \cup O$
K	The set of EVs, $K = \{1,\ 2,\ \ldots,\ p\}$, $k \in K$
Parameter	
d_{ij}	The distance between nodes i and j
t_{ij}	The travel time between nodes i and j
q_i	The demand of customer node i
a_i	Earliest service start time at customer i
b_i	Latest service start time at customer i
$s_i w_i t_i$	Service time at customer i with $s_0 = s_l = 0$
	The waiting time of an EV at customer i
	The arrival time of an EV at customer i
Q	The load capacity of an EV
B	The battery capacity of an EV
C	Vehicle capacity
h	Charge consumption rate
Decision Variables	
x_{ijk}	A binary variable indicating whether the EV travels from node i to node j
τ_i	The arrival time of EV at node i
y_i	The remaining battery capacity of EV at node i
u_i	The load of vehicle k after visiting node i

The mathematical model of the EVRPTW is formulated to address the complex challenge of optimizing routes for EVs while adhering to time constraints and considering vehicle capacities. Minimize the total distance traveled is the goal by the fleet of EVs while meeting all specified constraints. The model is defined as follows:

Minimize

$$f = \sum_{l} \sum_{j} \sum_{k=1}^{K} d_{ij} x_{ijk} \tag{1}$$

Subject to

$$\sum_{i \in V} x_{ijk} = \sum_{i \in V} x_{jik} = 1,\ \forall j \in V \tag{2}$$

$$\sum_{j} x_{0jk} = 1,\ k \in K \tag{3}$$

$$\sum_{i} x_{i0k} = 1,\ k \in K \tag{4}$$

$$\sum_{i \in V} x_{ijk} - \sum_{i \in V} x_{jik} = 0,\ \forall j \in V \tag{5}$$

$$0 \le u_j \le u_i - q_i x_{ijk} + Q(1 - x_{ijk}) \tag{6}$$

$$0 \le u_0 \le Q \tag{7}$$

$$y_0 = B,\ \ y_i = B,\ \ \forall j \in S,\ k \in K \tag{8}$$

$$y_i \le B,\ \ \forall j \in V,\ k \in K \tag{9}$$

$$0 \le y_j \le y_i - h d_{ij} x_{ijk} + B\,(1 - x_{ijk})\,,\ \ \forall i, j \in V,\ \ k \in K \tag{10}$$

$$0 \le y_j \le B - h d_{ij} x_{ijk},\ \ \forall i \in S,\ \ k \in K \tag{11}$$

$$a_i \le \tau_i + w_i \le b_i,\ \ \forall i \in V \tag{12}$$

$$w_i = max\ \{a_i - t_i, 0\},\ \ \forall i \in V \tag{13}$$

$$t_i = \tau_i,\ \ \forall i \in V \tag{14}$$

$$x_{ijk} \in \{0, 1\}\,,\ \ \forall i, j \in V,\ k \in K \tag{15}$$

$$u_i,\ y_i,\ \tau_i \ge 0,\ \forall i \in V. \tag{16}$$

This model integrates constraints for battery capacities, time windows, and route optimization to ensure that the routes are efficient and feasible for electric vehicles. The variables in the model represent decisions on vehicle routes, recharging points, and time windows, with the objective function aiming to minimize the overall distance traveled by the fleet. By addressing these factors, the model helps in formulating effective strategies for managing EV routes in logistics operations. The goal of the function of EVRP (1) is to reduce the total distance. Constraint (2) ensure that each customer visited by exactly one vehicle. Constraint (3) and (4) guarantee that each electric vehicle start and return at the depot. Constraint (5) guarantees that a single vehicle visits each customer, and that a single vehicle departs from its customer. Constraint (6) and (7) guarantee that the value is non-negative and does not exceed the vehicle's capacity, load upon arrival at any node, including the depot, ensuring that all customer needs are satisfied. Constraint (8) guarantees that an EV is fully charged before leaving the depot and the recharging station. Constraint (9) ensures that the battery charge level at any node during the route must always be within the battery's capacity limit. Constraint (10) and (11) ensure that the battery level is not zero and determined by the battery consumption and the vehicle's travel. Constraint (12)-(14) guarantee the time windows. Constraint (15) ensures a set of binary decision variables, where the value is 1 if the node is visited and 0 otherwise. Constraint (16) describes the battery level, time, and load capacity is non-negative.

2.2. Grasshopper Optimization Algorithm

The GOA algorithm is a population-based method that mimics the social behavior and hunting methods of grasshoppers, involving each grasshopper as a solution in the population, influenced by social interaction, wind advection, and gravity force [16]. The mathematical model used to calculate the position X_i of each solution:

$$X_i = S_i + G_i + A_i \tag{17}$$

where A_i stands for air advection, G_i for the solution's gravitational pull, and S_i for the social interaction between the solution and the other grasshoppers. The position of each solution after random behavior is added is represented by the equation below:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \tag{18}$$

where r_1, r_2, and r_3 are random numbers in $[0,\ 1]$. Let's now have a look at the model of each force used in eq. (17). The force of social interaction S_i, the equation below represents the social interaction between the solution and the other grasshoppers:

$$S_i = \sum_{j=1}^{N} s\left(d_{ij}\right)\widehat{d_{ij}},\ \text{where } i \neq j. \tag{19}$$

$$s = fe^{-\frac{r}{l}} - e^{-r} \tag{20}$$

Where d_{ij} is the distance between the $i-th$ and the $j-th$ grasshopper, calculated as $d_{ij} = |x_j - x_i|$, and $\widehat{d_{ij}} = \frac{x_j - x_i}{d_{ij}}$ represents the unit vector. In addition, s represents the strength of two social forces (repulsion and attraction between grasshoppers), where l is the attractive length scale and f is the intensity of attraction. In fact, these cofficients l and f have a great impact in the social behavior of grasshoppers. the second force, which is the force of gravity. The equation below shows how to calculate the force of gravity G_i:

$$G_i = -g\widehat{e_g} \tag{21}$$

where $-g$ represents the gravitational constant and $\widehat{e_g}$ is unit vector toward center of earth. The movements of nymph and adulthood grasshoppers are correlated with the wind direction A_i. The equation below shows how to compute A_i :

$$A_i = u\widehat{e_w} \tag{22}$$

where u represents the drift constant and $\widehat{e_w}$ is the unit vector in the wind direction.

$$X_i = \sum_{j=1}^{N} s\left(|x_j - x_i|\right)\frac{x_j - x_i}{d_{ij}} - g\widehat{e_g} + u\widehat{e_w} \tag{23}$$

In order to solve optimization issues and prevent grasshoppers from quickly reaching their comfort zone and the swarm from failing to converge to the target location (global optimum), we'll make some modifications in eq. (23):

$$X_i^d = c\left(\sum_{j=1}^{N} c\frac{UB_d - LB_d}{2} s\left(\left|x_d^j - x_i^d\right|\right)\frac{x_j - x_i}{d_{ij}}\right) + \text{Best Solution}, \tag{24}$$

where $G = 0$, A is the best solution in the $d-th$ dimension, and UB_d and LB_d are the upper and lower bounds in the $d-th$ dimension, respectively. The parameter c represents the decreasing coefficient, and it is in charge of decreasing the comfort zone, repulsion zone, and attraction zone. In order to balance the exploration and the exploitation phases using the grasshopper approach, the coefficient c decreases according to the number of iterations. Here's the model for c:

$$c = c_{max} - iter\frac{c_{max} - c_{min}}{Max_{iter}} \tag{25}$$

where c_{max} and c_{min} are the maximum and minimum values of c respectively, $iter$ is the current iteration, and Max_{iter} is the maximum number of iterations.

3. Results and Discussion

The study utilized Solomon benchmark problem set [18]. The dataset is still designed for conventional vehicles as it lacks electric charging data. To adapt it for electric vehicles, a number of charging stations were randomly selected for this experiment. Represented by $x \in X_c$ and $y \in Y_c$, where X_c and Y_c correspond to the range of customer coordinates *X* and *Y*, respectively. We modified three specific sets of these benchmark instances for the EVRPTW. Solomon's benchmarks for clustered data types (C types) compared to randomly distributed data types (R types) and both (RC types). These categories include data on the number and capacity of vehicles as well as detailed information regarding each customer's location, demand, time window, and service time. Each type uses type series 101, 102, 201, 202 and includes one depot, and and 3 charging stations. The study compares the effectiveness of the GOA method for solving EVRPTW with 25 customers and 50 customers. The parameters are using the value of $c_{min} = 0.00004$ and $c_{max} = 2$. The upper limit dimension $(UB_d) = 5$, and the lower limit dimension $(LB_d) = -5$, while for many grasshoppers there are 500 and Max_{iter} to 100. The experimental results for 25 customers across two datasets from each data category are presented in Table 2. The table shows the number of vehicles (NV) and total distance traveled. Similarly, the experimental results for 50 customers across two datasets from each data category are summarized in Table 3. The results show that the GOA is more efficient in terms of vehicle requirements and total distance traveled. These findings offer insight into the GOA's performance across different problem sets and customer sizes.

The GOA algorithm shows competitive performance in terms of vehicle utilisation, with results equal to or less than the most well-known Solomon solution. However, in EVRPTW, the total distance travelled is longer due to the presence of recharging stations. GOA produces solutions close to Solomon's for certain types of random data, but is more difficult for scenarios involving 50 customers. It can be seen in Table 3 that the total distance for 50 customers is very long and the process is lengthy. This algorithm is more suitable for small-scale data problems, especially for clustered data types. Further analysis of the performance across larger data sets may provide insight into the potential improvements and adaptability of GOA to different data distributions.

Table 2. Experimental result for 25 customers

No	Problem	GOA	
		NV	Distance
1	C101	3	321.40
2	C102	3	318.30
3	C201	1	336.80
4	C202	1	309.90
5	R101	2	656.50
6	R102	2	673.40
7	R201	1	889.70
8	R202	1	743.50
9	RC101	3	511.90
10	RC102	3	638.40
11	RC201	1	1159.70
12	RC202	1	986.20

Table 3. Experimental result for 50 customers

No	Problem	GOA	
		NV	Distance
1	C101	5	611,4
2	C102	5	539,5
3	C201	2	817,5
4	C202	2	624,3
5	R101	4	1490,9
6	R102	4	1468,1
7	R201	1	1843,7
8	R202	1	1750,5
9	RC101	6	2033,3
10	RC102	6	2003,3
11	RC201	1	3010,4
12	RC202	1	2549,1

For data type C101, the solution produces a route with NV = 3 and a total distance of 321.40. The C101 route visits one charging station (CS) for route 1 and 2. The route details for 25 customers in the C101 data type are as follows:

R1 = [Depot, 20, 5, 3, 25, 7, 8, 10, 11, 9, CS2, 6, 23, 21, Depot]
R2 = [Depot, 24, 18, 19, 15, 16, 12, 4, CS2, 2, 1, Depot]
R3 = [Depot, 13, 17, 14, 22, Depot]

For data type R101, the solution produces a route that has NV = 2 and the total distance is 656.50. The R101 visit all the charging station it makes the total distance larger. The route details for 25 customers in the R101 data type are as follows:

R1 = [Depot, 14, 5, 2, CS3, 15, 21, 23, 16, CS3, 18, 8, 22, CS3, 6, 17, 13, 1, Depot]
R2 = [Depot, 12, 11, 19, 7, 9, CS2, 3, 10, 20, 4, CS1, 24, 25, Depot]

In the application of EVRPTW using GOA, different results were obtained for two data types: C101 and R101. For the C101 data type, the solution produced a route with 3 vehicles and a total distance of 321.40. In this route, only Route 1 and Route 2 visit a charging station (CS2), while Route 3 does not require recharging. For the R101 data type, the solution uses 2 vehicles but results in a much larger total distance of 656.50. This increase in distance is due to the frequent visits to charging stations (CS1, CS2, and CS3). This contrast highlights the impact of customer distribution and charging station locations on EV route efficiency. Fewer vehicles, as in R101, increase total distance due to frequent recharging. Optimizing charging station placement can enhance efficiency.

The results were obtained for the C101 and R101 data types with 50 customers. For the C101 data type, the solution uses 5 vehicles, which is the same as in the 50-customer dataset, with a total distance of 611.40. All routes visit charging stations, ensuring that the vehicles meet their battery constraints while covering the necessary customers. The route breakdown is as follows:

R1 = [Depot, 8, 27, 19, 15, 16, 9, CS2, 6, 36, 2, CS1, Depot]
R2 = [Depot, 20, 32, 3, CS1, 33, 31, 40, 44, 45, 39, CS3, 48, 50, 47, Depot]
R3 = [Depot, 43, 42, 41, 18, 35, CS3, 10, 29, 37, 46, CS3, 26, 23, 34, 49, Depot]
R4 = [Depot, 5, 13, 17, 11, 38, CS3, 28, 14, 12, 4, 51, 1, 21, Depot]
R5 = [Depot, 24, 25, 7, 30, 22, Depot]

This solution demonstrates that, despite visiting all charging stations, the overall distance remains controlled. The use of five vehicles allows for a balanced distribution of customers across the routes, with strategic visits to the charging stations to maintain vehicle energy levels.

For the R101 data type, the solution involves 4 vehicles and a significantly larger total distance of 1490,9. The increased distance can be attributed to the frequent visits to multiple charging stations, which are necessary to meet the energy demands over the longer routes. The routes are as follows:

R1 = [Depot, 42, 14, 45, 2, CS3, 47, 11, 19, CS3, 7, 49, 46, 10, CS2, 43, 48, CS3, Depot]
R2 = [Depot, 27, 33, 36, CS3, 31, 21, 12, 40, CS3, 18, 9, 34, 20, CS2, 26, 37, 32, CS2, 17, Depot]
R3 = [Depot, 5, 28, 15, CS3, 23, 44, 16, 38, CS3, 41, 22, 6, 50, 51, 35, 24, 1, 25, 51, Depot]
R4 = [Depot, 39, 29, 30, CS2, 8, 3, 4, CS1, 13, Depot]

The higher total distance in R101 is due to the longer travel distances between customers and the necessity to frequently recharge the vehicles. The 4-vehicle solution, while minimizing the number of vehicles, leads to extended routes with multiple charging stops, particularly in R1 and R3, where vehicles return to charging stations several times. In both C101 and R101, the GOA based solution shows that frequent visits to charging stations significantly impact the total distance. For C101, the use of 5 vehicles helps distribute the customer demand effectively, limiting the total distance. In contrast, for R101, the use of 4 vehicles results in longer routes and more frequent recharging, thus inflating the total distance. These results suggest that optimizing the number of vehicles and strategically planning charging station visits are crucial in minimizing the total distance in EVRPTW problems.

4. Conclusion

The experimental results highlight the effectiveness and limitations of the GOA in solving the EVRPTW. GOA shows competitive vehicle utilization like Solomon's benchmarks, but its total distance minimization depends heavily on customer and charging station distribution. Increasing the number of customers increases the route complexity and total distance traveled. At 25 customers, types C, R, RC are quite efficient although R and RC result in longer distances due to high recharge frequency. At 50 customers, the total distance increases dramatically, especially for the R and RC types. This shows that GOA is suitable for small to medium scale problems, but faces scalability challenges on larger datasets. To improve GOA for large-scale EVRPTW, future research should develop hybrid metaheuristics that integrate adaptive recharging, better vehicle allocation, and dynamic charging station placement. These adjustments could boost efficiency and balance minimizing vehicles with reducing travel distance.

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