Palestine Journal of Mathematics

Vol 14 (Special Issue IV), (2025) , 139–148

METAHEURISTIC APPROACH FOR EFFICIENT BATTERY-DRIVEN AUTOMOBILES WITH SCHEDULING CONSTRAINTS HAVING MULTI CHARGING STATIONS

Mohit K. Kakkar and Priyanka

MSC 2010 Classifications: Primary 33C20; Secondary 33C65.

Keywords and phrases: EVRPTW, Genetic Algorithm, Sustainability, Charging Stations, Distribution Centre.

The authors would like to thank the reviewers and editor for their constructive comments and valuable suggestions that improved the quality of our paper.

Abstract *Transportation is a form of activity that is linked to logistics operations in one way or another. Logistical companies were broadening the range of the items delivered using the fleets of electric vehicles due to the new legislative frameworks and emission reduction targets. A last-mile delivery focus is mainly given to such vehicles that derive their power from batteries. The Electricity-based Vehicle Routing Problem (EVRP) is a special case of VRPs concerned with sustainability aspects of transportation. EVRP aims to balance economic and environmental costs by developing alternatives that address these concerns. In this paper, an electric vehicle fleet with time constraints, multi- charging stations, and multi-depots with penalties also for early and late arrivals is presented. Since the problem is rather complicated, the metaheuristic algorithm is used to achieve the best results. Based on the computational results, this method was found to be suitable for small- scale and large-scale instances.*

1 Introduction

Over the past few years, the global focus on environmental sustainability and the optimization of logistical operations has been intensified, prodding the transportation industry to gain innovative solutions that help minimize the carbon footprint, meanwhile enhance operational efficiency. One of those challenges is the Time-restricted automobile routing issue, a variation of the Vehicle Routing Problem (VRP) [24] that deals with optimizing the routes of a vehicle in delivering the goods, minimizing the costs, and maximizing the efficiency. Time windows constrain delivery or pickup times at the customer's location.
The leading motive of this research document is to address the EVRPTW by applying novel optimization approaches that help in balancing environmental sustainability, operational efficiency, and cost- effectiveness. By imposing advanced algorithms and metaheuristic techniques, we aim to develop strategies that minimize carbon emissions, optimize vehicle utilization, and meet customer-level service within the specified time. This problem relates to the category of NP-Hard problems. The research related to VRPs and a variety of algorithms used to find the optimal solutions to many real-life problems. Section 2 refers to the Methodology containing the parameters and the constraints that are used in this research paper. The objective function is also defined here in which the prior motive is to reduce the overall travelling duration and the time taken by it to recharge the battery at the corresponding charging stands and the service that is provided at the customer's location and the charging stations. Section 3 is the algorithm that is taken into consideration to find the optimality of the problem. Section 4 refers to the solution method and the algorithm's steps. Section 5 provides the outcomes of computational experiments on different instances and a table is also presented for the outputs. Lastly, Section 6 refers to the conclusion of the research paper that we have derived from our research.
The Vehicle Routing Challenge-VRC was first proposed by [5]. They worked with the capacitated vehicle routing problem (CVRP) [5]. Thereafter, so many researchers published their research papers related to this topic. Further modifications were made and the problem reached to Capacitated Vehicle Routing Problem with duration limitation. Now the CVRPDL are the vehicle routing problems having scheduling constraints where the delivery man must deliver the products in a particular period. As the research progressed to more advanced stages, the difficulty of the topic also increased and many metaheuristic approaches came into existence. These metaheuristic approaches were Genetic Algorithms, Tabu Search, Simulated annealing, and Adaptive Large Neighbourhood Search. Now comes the Multi- Compartment Vehicle Routing Problem which was introduced by [7] that described an MCVRP in which the distribution of animal foods to farms where the spaces for chambers and the corresponding assignment of product types to the chambers were allotted in advance. They proposed a memetic algorithm and Tabu search to obtain stable results for the given problem. Green Vehicle Routing Problems were also taken into consideration [6] to maintain the sustainability of the environment. Electric VRPs aim to focus on the reduction of fuel consumption and CO2 emissions. Miller Hooks and Erdogan gave a new approach to solving such problems.

They used Modified Clarke and Wright Savings Algorithm and Density Based Clustering Algorithm. The Clarke and Wright Savings Algorithm was generated for traditional VRPs and specialized for its types and is updated to generate the MCWS method to deal with the obstacles introduced by the Green Vehicle Routing Problem. In 2014, [22] worked on the EVRP with Time windows, where they used a hybrid metaheuristic algorithm which was a combination of variable neighbourhood search algorithm and tabu search. They also took the benchmark conditions. [4] in 2011 also worked with *transportation problems with capacity constraints and the vehicles were allowed to recharge at the customer's location. The main aim of this article was to reduce the distance and transportation costs. [9] in 2015 introduced electric vehicle routing problem had dependent constraints with a heterogenous fleet of electric vehicles and fuel such as diesel and petrol vehicles. They used the adaptive neighbourhood search method to find optimality. [20] 2018 proposed a hybrid genetic algorithm for smart freight delivery using electric vehicles. Here the researchers used the best route crossover operator along with the variable neighbourhood search algorithm to find the solutions. In 2016, [11] also worked on electric vehicles using the adaptive large neighbourhood search. They mainly focused on the partial recharging of the vehicles and time window constraint was also considered. In 2016, EVRP was also taken into knowledge by [12], where they studied the case of vehicles in Austin, Texas. Researchers found that EVRP is better as compared to diesel trucks.*

[17] worked on the non-linear charging functions for electric vehicles where they found that ignoring non- linear charging functions leads to over-expensive solutions. Moving further, in 2020, [13] tried to find the optimality for larger instances using an iterated variable neighbourhood search algorithm that includes a fast evaluation method. They used the constraint of a time window along with a benchmark problem of 40 instances. Shuai Zhang et al. [25] 2018 generated a meta- heuristic algorithm using an ant colony algorithm to find the best routes for a routing problem using electric vehicles. They also computed the difference between the objective functions of minimizing energy consumption and the distance. In 2017, [23] preferred to work on the charging time and the travel time. The scholars used the Dijkstra method to find the shortest path and they did a case study of the region of Beijing, China. Furthermore, [21] in 2022 investigated the results by using a fleet of electric vehicles by applying a variable neighbourhood search algorithm along with the tabu search. They also gave a case study of Nottingham, United Kingdom. Another important issue that was thought of by [8] in 2023 was energy differences at different charging stations. They tried the improved ant colony algorithm and observed that it worked well and gave better answers to the problems. A greedy search algorithm was also used by [10] to find the solutions in 2023. Researchers used benchmark data they obtained from the CEC – 12 Tram Routing Problem. In 2023 only, new research was also developed by [3]. In this paper, they considered a Multi- Depot Green Vehicle routing problem with time windows having time variations due to the road networks. They applied the Genetic Algorithm along with the simulated annealing to obtain the solution of the Problem. [2] also worked on the electric VRP considering a mixture of Conventional and electric vehicles. They took into concern a reality problem in the areas of Ontario and Greater Toronto of Canada. Multi-objective approaches, encompassing Weighted sum, ϵ-constraint , and metaheuristic approaches, are incorporated into Adaptive Large Neighbourhood Search (ALNS) to address this bi- objective problem. One more article was written in 2023 by [14]. They have considered conventional vehicles and Electric vehicles with road restrictions. They used adaptive large neighbourhood search and found optimized results in CPLEX. ***Figure 1*** *and* ***Figure 2*** *describes the difference between the routes of vehicles withou visiting and with visiting recharging stations.*

2 Proposed Methodology

The e-VRP with a time window includes detections of admissible routes of the e-vehicles along with the minimization of travelling and the penalty costs for breaking the time window of each customer. The reference of the proposed model is taken from [26] where the authors have also worked on the electricity-based vehicle routing problem with time window and penalty charges.

PARAMETERS:

C = Collection of all Vertices, $C = M \cup S \cup D$
M= Collection of Customer Nodes
S= Analogue consists of charging Stations
D= Collection of Depots
V= Collection of Electric Vehicles
K= Unit cost of the Electric Vehicles per kilometre
s_{mn} = Distance between node m and node n $\quad \forall m, n \in C$
d_m = requirement of customer m $\quad \forall m \in M$
B= Loading Proportion of an Electric Vehicle
Q= Battery Proportion of Electric Vehicle
q^1_{cw}, q^2_{cw}= Energy of Electric Vehicle w reaching and departing nodes respectively
r_m, t_m = A time window of the customer node m $\quad \forall m \in M$
rqv = Unit penalty charges every hour for reaching before and late than the given time window respectively
e^*_m, e^{**}_m = The arrival and departing time of the e-vehicle at the node m $\quad \forall m \in C$
ek_m = Waiting period for the Electric vehicle at the node m $\quad \forall m \in M$
eh_m = Service time at node m $\quad \forall m \in M \cap S$
e_{mn} = Travelling time from m to n $\quad \forall m, n \in C$
Velocity = Travelling Speed of the Electric Vehicle

Decision Variables:

$$y_{mnw} = \begin{cases} 1, & \text{if EV } w \text{ visits node } n \text{ after the node } m, w \in V, m, n \in C \\ 0, & \text{otherwise} \end{cases}$$

$$g_{wm} = \begin{cases} 1, & \text{if Electric vehicle } w \text{ visits node } m, \forall w \in V, m \in M \\ 0, & \text{otherwise} \end{cases}$$

The formulation of methodology for EVRPTW is as follows:

$$min\hat{Z} = K \sum_{w \in V} \sum_{m \in C} \sum_{n \in C} y_{mnw} s_{mn} + \sum_{w \in V} \sum_{m \in M} qv_m(e_m) \tag{2.1}$$

such that

$$\sum_{w\in V}\sum_{m\in C} y_{0mw} - \sum_{w\in V}\sum_{n\in C} y_{n0w} = 0, \forall k \in S_k \tag{2.2}$$

$$\sum_{w\in V,\ m\neq n} y_{mnw} = 1, \forall n \in C, \forall w \in V \tag{2.3}$$

$$\sum_{m\in M} q_{wm} \cdot d_m \leq B, \forall w \in V \tag{2.4}$$

$$\sum_{w\in V}\sum_{m\in C,\ m\neq 0} y_{0mw} \leq |V| \tag{2.5}$$

$$\sum_{m\in M}\sum_{n\in M,\ n\neq m} y_{mnw} \leq |M|, \forall w \in V \tag{2.6}$$

$$e_0^{**} = 0 \tag{2.7}$$

$$e_{mn} = s_{mn}/velocity, \quad \forall m, n \in C \tag{2.8}$$

$$e_m^{**} = e_m^* + eh_m + ek_m, \quad \forall m \in M \cap S \tag{2.9}$$

$$e_n = \sum_{m\in C}\sum_{n\in C,\ m\neq n} y_{mnw}(e_m^{**} + e_{mn}), \quad \forall w \in V \tag{2.10}$$

$$e_{km} = max[0, (r_m, e_m^*)], \quad \forall m \in M \tag{2.11}$$

$$qv_m(e_m^*) = rqv \times max(r_m - e_m^*, 0) + tqv \times max(e_m^* - t_m, 0) \tag{2.12}$$

$$q_{mw}^1 = q_{mw}^2, \quad \forall m \in M, \forall w \in V \tag{2.13}$$

$$q_{mw}^2 = Q, \forall m \in D \cap S, \quad \forall w \in V \tag{2.14}$$

$$q_{cw}^1 \geq 0, \forall c \in C, \quad \forall w \in V \tag{2.15}$$

$$y_{mnw}, g_{wm} \in \{0, 1\}, \quad \forall m, n \in C, \forall w \in V \tag{2.16}$$

The main objective (2.1) of the problem consists of two parts, hence it is called a bi-objective problem. The initial portion is the addition of all the driving charges of the electric vehicles from one point to any other point. The second portion depicts the penalty cost whenever the electric vehicle fails to fulfil the time-dependent constraint. Equation (2.2) makes sure that the electric vehicle initializes and ends its delivery at the central depot. Equation (2.3) depicts if any e-vehicle goes to a consumer once only. Equation (2.4) ensures that the demand of each customer must be satisfied by an electric vehicle. The number of e-vehicles in service must not surpass the number of e-vehicles present at the depot. Equation (2.5) restricts this condition. Equation (2.6) warrants that electric vehicles do not have the authority to serve customers more than the customer number defined. In equation (2.7), the starting delivery time at the depot is set to zero. Equation (2.8) reveals the travelling time from node m to node n. Equation (2.9) guarantees that the departing time of the node must consider the initial time, delivery time, and waiting time. Equation (2.10) considers the reaching time at the next node must be equivalent to the departing time of the previous node including the tour time. Equation (2.11) limits the waiting time at the consumer node if the electric vehicle comes before the time window. Equation (2.12) depicts the punishment cost for breaking the time window. Equation (2.13) gives the point that the energy is not consumed at the consumer nodes. Equation (2.14) ensures that an electric vehicle must be fully charged to its maximum capacity. Constraint (2.15) ensures that the available battery energy is positive on any node. Part (2.16) declares that the value of y_{mnw} and q_{wm} are binary i.e. either one or zero.

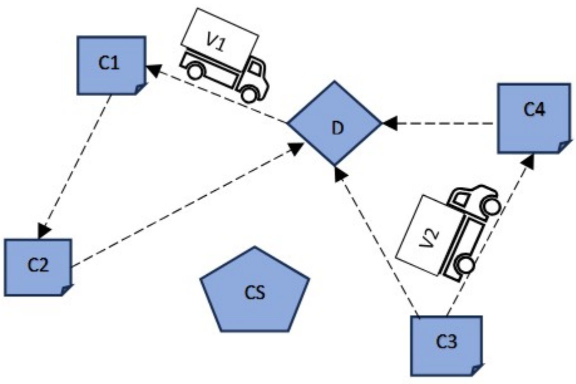

Figure 1. Without visiting the recharging station

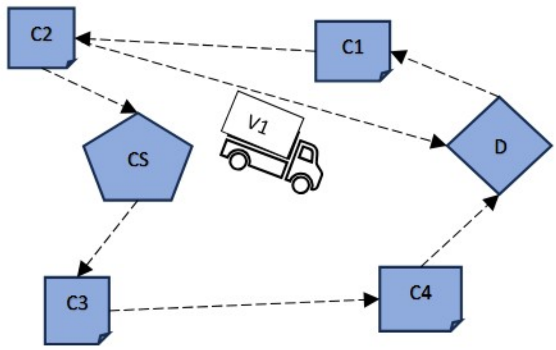

Figure 2. Visiting the Recharging Station

Here,

C1, C2, C3, C4= Clients

V1, V2= Vehicles

D= Central Depot

CS= Charging Station

3 Genetic Algorithm

Metaheuristic approaches are crucial for solving mathematical optimization problems. Genetic algorithms are one of them. These algorithms have a rich history, filled with innovation, and have progressed over time. Genetic Algorithms came into existence with the work of John Holland at the University of Michigan in the 1960s. He started his work by establishing relationships between natural selection and the optimization processes. In 1962, Holland published his book "Adaptation in Natural and Artificial Systems" in which he unveiled the basic concepts of genetic algorithms and their applications to machine learning and optimization techniques. The genetic algorithm is based on several key components, which include the chromosomes, fitness calculation, choosing individuals for reproduction, crossover operators, and mutation operators. All these components work iteratively to solve an NP-Hard problem to find optimal or near-optimal solutions. There are variants in the crossovers of the genetic algorithms such as single- point crossover, double-point crossover, uniform crossover, and average crossover. All the crossovers work according to the given conditions and the requirements of the problem. The steps involved in the genetic algorithm are initialization, Fitness evaluation, Selection, Crossover, mutation, Replacement, Termination, and the output. Initialization is the step where the initial population is generated. In the second step, we calculate fitness of parents, third move involves the selection of the best parents. In the next step, create the new offspring from the selected individuals. Furthermore, introduces random changes to maintain the diversity. Replacement involves the selection of new individuals for the next generation. Finally, repeat the process until the best solution is found. Genetic algorithms have played a crucial role in many fields related to optimization techniques and machine learning. In multi-objective optimization problems, genetic algorithms help to optimize the given objectives simultaneously. Vehicle routing Problems are one of the main issues related to optimization techniques where the genetic algorithms have their own importance. Genetic algorithms inspired by the natural selection process, present a strong optimal method for the GVRP that guarantees the best solution to any given multi-objective problem. Many researchers have applied genetic algorithms to find optimal values in findings of the distance travelled, and minimize the travel cost, and in the case of electricity-based vehicle routing problems, many researchers have used genetic algorithms. One of the published papers is [19] in which the scholars have used the nature-based approach to find the best solutions. In this research article, they have proposed a genetic algorithm-based solution for a basic model of alternate- fuel consumption vehicle routing optimization problem. Apart from this success, genetic algorithms also have some drawbacks such as premature convergence and scalability issues. [18] also preferred genetic algorithms for their research work in software defect prediction models. They presented a summary of 26 GP-based SDP techniques and got a performance score of 71%. It is also applicable in the clustering of text documents; this application is used by [1] where the researchers have used a hybrid genetic algorithm where they have noticed that the accuracy with alone hybrid similarity is 72.34and along with genetic algorithm similarity is 84.14%. Future research must address these challenges and add new algorithmic variants, applying genetic algorithms to deep learning and machine learning. Genetic algorithms are still solving many complex optimization problems and driving innovation in many areas. **Figure 3** reveals the steps involved in genetic algorithm. These algorithms are primed to remain a strong tool to solve optimization issues in the upcoming years.

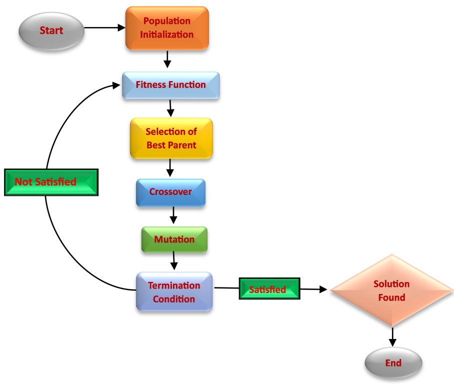

Figure 3. Procedure of Genetic Algorithm

4 Solution Approach

As it is known that the electricity-based automobile routing problem has difficult conditions, we applied the genetic algorithm to find its solution.
In our solution approach, we have taken the depot as the starting point |0|, the recharging area {c+1, c+2, c+3, ..., c+d} and the customer nodes {1,2,3,4,..., c} are encoded by the chromosome by a natural number. The sequence of visiting customers is represented by a sequence of the values of genes. **Table 1** points out a chromosome that gives the solution of three routes which include (1) (0-4-3-8-2-0). EV 1 starts its path from the starting point i.e. depot and reaches consumer nodes 4 and 3. After having a quick recharge, it comes to consumer node 2 and comes back to the depot |2| (0-9-5-6-7-0). Now, electric vehicle 2 firstly visits the customer node 9 and gets recharged. After finishing its work at node 6 and node 7 it returns to the depot |3| (0-1- 10-0). The path of the electric vehicle 3 is node 1 and node 10 without getting its battery charged.

0	4	3	8	2	0	9	5	6	7	0	1	10	0

Table 1. Genetic Encoding of a Solution

The Process of the proposed Genetic Algorithm is explained below:
Step 1: Population Initialization. Create an initial population by randomly orienting the codes of recharging stations and customer nodes in the genes. As d_m represents the requirement of the customer node m, (c-1)) times and parallelly add the number zero in the primary and the terminal genes to construct the first individual. The first step which is initialization guarantees that the customer demand is fulfilled and the loading capacity of an electric vehicle is also not exceeded.
Step 2: Fitness Evaluation: The main concern of the evaluation is the objective function. In this research work, we impose a penalty cost along with the constraint of loading capacity and the distance travelled by electric vehicles. The updated objective is as follows:

$$min\hat{Z} = K\sum_{w\in V}\sum_{m\in C}\sum_{n\in C} y_{mnw}s_{mn} + \sum_{w\in V}\sum_{m\in M} qv_m(e_m) + S_1\cdot max(\sum_{m\in M} d_m - B, 0) + S_2\cdot max(-q^1_{cw}, 0) \tag{4.1}$$

Where S_1 and S_2 are limitless positive numbers.
Let us define the fitness function as:

$$min\hat{Z} = 1/fit(m) \rightarrow fit(m) = 1/min\hat{Z} \tag{4.2}$$

The fitness value is just inversely proportional to the objective of the problem. It gives us an appropriate solution.
Step 3: Selecting Best Parent: The roulette Wheel selection strategy is applied to choose the best parent to recreate the worst offspring. The steps involved in the selection process are as:
(1) Find the best fit solution *fit(m)* of each individual. (2) Add all the fitness values as

$$Cumfit = \sum_{m\in M} fit(m), m = 1, 2, 3, \ldots, c \tag{4.3}$$

(3) Calculate the possibility of each being chosen as the best individual

$$q(m) = fit(m)/Cumfit, m = 1, 2, 3, \ldots, c \tag{4.4}$$

(4) Determine the cumulative probability of the present population

$$cp(m) = \sum_{m\in M} q_m, m = 1, 2, 3, \ldots, c \tag{4.5}$$

(5) Randomly produce a real number x . In case cp$(m) > x$,then choose the first chromosome, otherwise switch to the chromosome that satisfies the condition:
cp$(m-1) < x < cp(m)$.
Step 4: Crossover: Crossover is an essential part of the genetic algorithm as it gives new solutions for the existing parents. Here, we combine the genetic information of two parent chromosomes to generate a modified offspring chromosome.

Different kinds of crossovers are- single-point crossover, multi-point crossover, uniform crossover, and arithmetic crossover. Crossover involves following steps:

SINGLE POINT CROSSOVER:

Firstly, choose arbitrarily a partition of genes in the individuals.

0	3	4	8	2	0	9	5	6	7	0	1	10	0

0	4	3	2	8	0	9	5	6	7	0	1	10	0

Table 2. Random selection of parents 1 and 2

The next step is to choose the crossover point. Randomly chose the crossover point as 5. After that, divide the parent chromosomes into two parts. The first step includes the parents till the crossover point and the second involves the portion after the crossover point. Parent 1 up to the crossover point involves

0	3	4	8	2

and after the crossover point the portion includes

0	9	5	6	7	0

Similarly, parent 2 genes up to the crossover point have the part

0	4	3	2	8

and after crossover, it includes

0	9	5	6	7	0	1	10	0

Finally generated offspring are formed by the criteria as- offspring 1 formed with parent 1 up to crossover point and parent 2 after crossover point. Same as 1, offspring 2 is formed with parent 2 up to crossover and parent 1 after crossover point. Resulting Offsprings are:

0	3	4	8	2	0	9	5	6	7	0	1	10	0

0	4	3	2	8	0	9	5	6	7	0	1	10	0

Table 3. Offsprings 1 and 2

As we want to minimize the value of the objective function, therefore, offspring having the largest fitness value is to be selected.

Step 5: Mutation: The mutation operator elaborates on experimenting and it can manage trends of search. Take the mutation rate randomly. Here we have used the value of mutation rate = 0.1% (10% chances of mutation per gene). We can randomly change the value of the gene for mutation.

Create the mutated offspring 1:

Gene 3: $4 \rightarrow 5$ (mutated)
Gene 7: $6 \rightarrow 3$ (mutated)
Gene 10: $10 \rightarrow 9$ (mutated)

0	3	5	8	2	0	9	4	6	7	0	1	10	0

Create the mutated offspring 2:

Gene 2: $3 \rightarrow 2$ (mutated)
Gene 9: $5 \rightarrow 4$ (mutated)

0	4	2	2	8	0	9	4	6	7	0	1	10	0

Hence, the new generation is:

0	3	5	8	2	0	9	4	6	7	0	1	10	0

0	4	2	2	8	0	9	4	6	7	0	1	10	0

Table 4. Newly Generated Generations

Step (4) for DOUBLE POINT CROSSOVER:
Again, choose randomly a portion of genes in the individuals.

0	3	4	8	2	0	9	5	6	7	0	1	10	0

0	4	3	2	8	0	9	5	6	7	0	1	10	0

Table 5. Random Selection of Parent 1 and Parent 2

Now in double point crossover, randomly select two crossovers. Suppose the **crossover points are 3 and 9**. Create the offspring chromosomes by joining genetic information. Offspring 1 is generated by combining Parent 2 up to crossover point + Parent 1 between crossover point + Parent 2 after crossover point 2. Similarly, Offspring 2 is constructed by joining Parent 1 up to crossover point 1 + Parent 2 between crossover point + Parent 1 after crossover point.
Newly generated offspring are:

0	4	3	8	2	0	9	5	6	7	0	1	10	0

0	3	4	2	8	0	9	5	6	7	0	1	10	0

Table 6. Offsprings 1 and 2

Step 5: Mutation:
The next step involves the mutation process. Take the mutation rate as 0.1% (similar to in the case of Single Point Crossover)

Mutated Offspring 1:
Replace the existing gene values with new values.
Gene 5: $5 \rightarrow 3$ (mutated)
Gene 9: $7 \rightarrow 9$ (mutated)
Offspring 1:

0	4	3	8	2	0	9	3	6	9	0	1	10	0

Mutated Offspring 2:
Repeat the process and replace the values of the existing genes.
Gene 2: $4 \rightarrow 5$ (mutated)
Gene 11: $1 \rightarrow 2$ (mutated)
Offspring 2:

0	3	5	2	8	0	9	5	6	7	0	1	10	0

Hence, the newly generated generation is:

0	4	3	8	2	0	9	3	6	9	0	1	10	0

0	3	5	2	8	0	9	5	6	7	0	1	10	0

Table 7. Offsprings 1 and 2

High mutation rates give good solutions and slow down the convergence of the algorithm.
Step 6: Stop: The newly created generation will go through all the steps again until the termination condition is reached or it can also be called an optimized solution or satisfactory solution.

5 Experimental Results

We tested our algorithm on some benchmark tasks. All of the problem situations consist of different clients, one depot, and uniform fleets. The geographical coordinates of the consumers and depots are provided in the form of (x, y). Their route length is calculated using Euclidean distance, which is measured in units of distance. The time taken to go one unit distance is regarded to be one unit time.
The proposed algorithms are written in the Python 3.6 programming language. To test its implementation, a machine with a 3 GHz i5 processor and 28 GB RAM was used.
This study analysed some EVRP cases using the dataset like E-n22-k4, which included 22 nodes, 4 vehicles, and 8 charging stations. The system consists of 22 nodes, with one depot serving as the departure and arrival site for each vehicle. Some characteristics utilized in [15] (for example, energy consumption rate and maximum energy capacity) change slightly from those used in [16]. The values from [15] are used to solve the instances we used in this work. **Figure 4** and **Figure 5** presented the shortest route path for two instances E-n22-k4 and E-n51-k5. For E-n22-k4 we have used the following parameter values
vehicles: 4
clients: 22
charging stations: 8
capacity: 6000
energy_capacity: 94
energy_consumption: 1.20
Table 8 displays the results for various EVRP dataset sizes. Column one of this table includes information about the problem instance and size. This table describes how the proposed GA metaheuristic performed on all the dataset's available instances [15].
Table 8 presents the results for the E occurrences. The best-known results for these instances values are displayed in the left-most column. Our proposed GA metaheuristic resulted in closed solutions for 2 out of 4 occurrences, as shown in **Table 8** with bold values for instances E-n22-k4 and E-n30-k3.

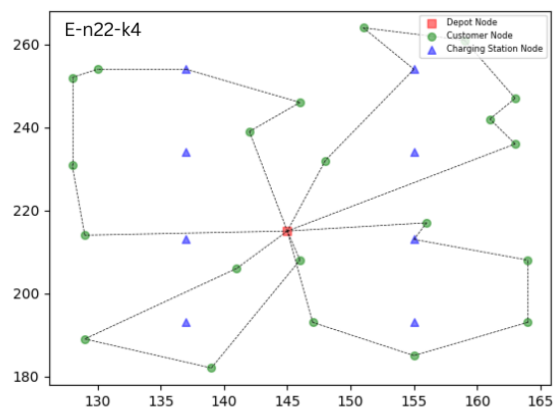

Figure 4. Shortest vehicle routes for instance E-n22-k4 with one depot

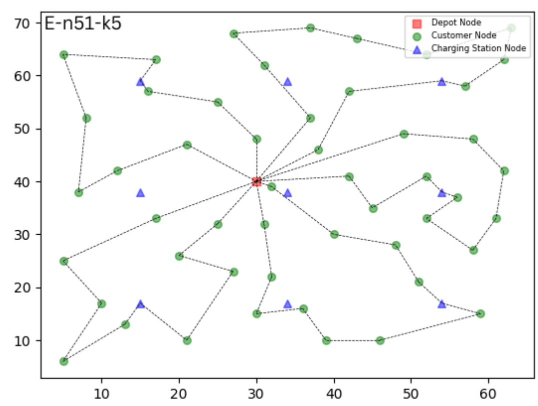

Figure 5. Shortest vehicle routes for instance E-n51-k5 with one depot

Instances	Best Known Results [15]	Proposed Algorithm		
	Minimum (Best)	Minimum (Best)	Maximum (Worst)	Mean
E-n22-k4	**384.67**	**385.09**	**390.62**	387.85
E-n30-k3	**509.47**	**509.54**	**509.54**	**509.54**
E-n51-k5	529.90	540.39	558.48	549.435
E-n101-k8	852.69	857.11	893.10	875.105

Table 8. Results for various EVRP datasets

6 Conclusion remarks

With the increased interest of today's logistic companies, a routing problem of electric vehicle fleets has evolved, known as electric vehicle routing (EVRP), which is an NP-hard combinatorial optimization problem. In this research work, we offer an efficient GA for solving EVRP while minimizing the overall distance travelled by the electrical vehicles. The proposed algorithm for solving the EVRP with a time window proved effective. The results we achieved were close to the ideal results of benchmark problems like E-n22-k4 and E-n30-k3. Also, we can see these solutions are good for a large-scale real-world problem like E-n101-k8 as well.

References

[1] D. Ahlawat, S. Chauhan and A. Kumar, *Improved Hybrid Similarity for Clustering of Text Documents Using GA*, International Conference on Emergent Converging Technologies and Biomedical Systems, 523–536, (2023).

[2] A. Amiri, S. H. Amin and H. Zolfagharinia, *A bi-objective green vehicle routing problem with a mixed fleet of conventional and electric trucks: Considering charging power and density of stations*,Expert Systems with Applications, **213**, 119228,(2023).

[3] C. M. Chen, S. Lv, J. Ning and J. M. T. Wu, *A genetic algorithm for the waitable time-varying multi-depot green vehicle routing problem,* Symmetry, **15(1)**, 124, (2023).

[4] R. G. Conrad and M. A. Figliozzi, *The recharging vehicle routing problem,* Proceedings of the 2011 industrial engineering research conference, **8** , 187–196, (2016).

[5] G. B. Dantzig and J. H. Ramser, *Dantzig, George B and Ramser, John H*, Management science, **6(1)** ,80-91 , (1959).

[6] S. Erdoğan and E. Miller-Hooks, *A green vehicle routing problem*, Transportation research part E: logistics and transportation review, **48(1)** , 100–114,(2012).

[7] A. El Fallahi, C. Prins and R. W. Calvo, *A memetic algorithm and a tabu search for the multi-compartment vehicle routing problem*. Computers & Operations Research, **35(5)**, 1725-1741, (2008).

[8] L. Fan, C. Liu, B. Dai, J. Li, Z. Wu and Y. Guo, *Electric vehicle routing problem considering energy differences of charging stations*, Journal of Cleaner Production , **418**, 138184, (2023).

[9] D. Goeke and M. Schneider, *Routing a mixed fleet of electric and conventional vehicles*, European Journal of Operational Research, **245(1)**, 81–99 , (2015).

[10] V. Q. Hien, T. C. Dao and H. T. T. Binh, *A greedy search based evolutionary algorithm for electric vehicle routing problem*, Applied Intelligence, **53(3)**, 2908–2922 , (2023).

[11] M. Keskin and B. Çatay, *Partial recharge strategies for the electric vehicle routing problem with time windows*, Transportation research part C: emerging technologies, **65** , 111–127,(2016).

[12] J. Lin, W. Zhou and O. Wolfson, *Electric vehicle routing problem*, Transportation research procedia,**12**, 508-521, (2016).

[13] J. Lu, Y. Chen, J. K. Hao and R. He, *The time-dependent electric vehicle routing problem: Model and solution*, Expert Systems with Applications,**161**, 113593 (2020).

[14] H. Ma, R. Yang, and X. Li, *Delivery routing for a mixed fleet of conventional and electric vehicles with road restrictions*, International Journal of Production Research, 1-24, (2024).

[15] M. Mavrovouniotis, and others, *CEC-12 competition on electric vehicle routing problem*, EVRPcompetition2020, (2020).

[16] M. Mavrovouniotis, C. Menelaou, S. Timotheou,G. Ellinas, C. Panayiotou and M. Polycarpou, *A benchmark test suite for the electric capacitated vehicle routing problem*, 2020 IEEE Congress on evolutionary computation (CEC), 1-8 (2020).

[17] A. Montoya, C.Guéret, J. E. Mendoza and J. G. Villegas, *The electric vehicle routing problem with non-linear charging function*, Transportation Research Part B: Methodological,**103**, 87-110, (2017).

[18] M. Pandit and D. Gupta, *Performance of genetic programming-based software defect prediction models*, International Journal of Performability Engineering,**17(9)**, 787, (2021).

[19] R. Prakash and S. Pushkar, *Solution to Multi-Objective GVRP With Genetic Algorithm and Time Window*, 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 1475-1482 (2021).

[20] D. Rezgui, H. Bouziri, W. Aggoune-Mtalaa and J. C. Siala, *A hybrid evolutionary algorithm for smart freight delivery with electric modular vehicles*, 2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA), 1-8 (2018).

[21] M. E. H. Sadati, V. Akbari and B. Çatay, *Electric vehicle routing problem with flexible deliveries*, International Journal of Production Research, **60(13)**, 4268-4294, (2022).

[22] M. Schneider, A. Stenger and D. Goeke, *The electric vehicle-routing problem with time windows and recharging stations*, Transportation science,**48(4)**, 500-520, (2014).

[23] S. Shao, W. Guan, B. Ran,Z. He and J. Bi, *Electric vehicle routing problem with charging time and variable travel time*, Mathematical Problems in Engineering,**2017(1)**, 5098183, (2017).

[24] P. Toth and and D. Vigo, *Vehicle routing: problems, methods, and applications*, athematical Problems in Engineering,(2014).

[25] S. Zhang, Y. Gajpal, S.S. Appadoo and M.M.S. Abdulkader, *Electric vehicle routing problem with recharging stations for minimizing energy consumption*, International journal of production economics,**203**, 404-413, (2018).

[26] G. Zhenfeng, L. Yang, J. Xiaodan and G. Sheng, *The electric vehicle routing problem with time windows using genetic algorithm*, 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 635-639, (2017).

Author information

Mohit K. Kakkar, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India.
E-mail: `mohit.kakkar@chitkara.edu.in`

Priyanka, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India.
E-mail: `priyanka.4968@chitkara.edu.in`