A Comparative Analysis of Methods for Solving the Electric Vehicle Routing Problem

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***Abstract*—The Electric Vehicle Routing Problem (EVRP) has gained significant attention in recent years due to the rapid growth of electric vehicles (EVs) and the associated challenges of efficiently planning their routes. The EVRP combines the classical Vehicle Routing Problem (VRP) with the additional constraints posed by electric vehicles, such as limited driving range and the need for recharging. This research paper presents a comprehensive comparison of various methods employed to tackle the EVRP. The objective is to identify the strengths and weaknesses of these methods, their applicability in different scenarios, and potential avenues for future research.**

***Index Terms*—Electric Vehicles, Heuristics, Local Search, Genetic Algorithm, Charging Stations Placement**

1. Introduction

With sustainability and the fight against climate change taking center stage globally, the widespread adoption of electric vehicles (EVs) has gained significant traction. EVs present a promising solution for curbing carbon emissions and reducing reliance on fossil fuels in the transportation sector. However, transitioning to electric mobility brings about a fresh set of logistical hurdles, one of which is known as the Electric Vehicle Routing Problem (EVRP) [1]. EVRP algorithms and models take into account various factors such as battery capacity, driving range, customer demands, traffic conditions, and charging station locations. These factors are carefully considered to develop advanced optimization models that aim to identify routing solutions that are both cost-effective and environmentally friendly for fleets of electric vehicles. M. Mavrovouniotis et al. [2] concentrate on the Electric Vehicle Routing Problem (EVRP) specifically designed for battery electric vehicles in recent studies addressing the routing problem of electric vehicle (EV) fleets, with the aim of promoting a more environmentally friendly, effective, and sustainable transportation system. The authors give a benchmark dataset to measure how well their suggested methods work. A combinatorial optimization problem known as the EVRP's goal of total distance minimization has been proven to be NP-hard.

Given the complexity of the EVRP, particularly when dealing with a large number of customers, heuristic algorithms provide effective solutions. Heuristic algorithms work by iteratively searching through the solution space, gradually refining potential solutions based on predefined rules or guidelines. These rules, known as heuristics, guide the search process by exploiting problem-specific knowledge and incorporating practical constraints. By prioritizing certain aspects of the problem, such as energy efficiency or charging station availability, heuristic algorithms can quickly generate feasible solutions that approximate the optimal solution.

Beside heuristic algorithms, the *Genetic algorithm* (GA) is also one of the most extensively studied in the scientific community. Inspired by natural selection and genetics, GA starts with a population of individuals that undergo reproduction and mutation to generate offspring. The process is repeated until a predefined termination condition is met. Over the years, GA has demonstrated remarkable success in obtaining optimal or near-optimal solutions for various complex real-world optimization problems, including combinatorial optimization, continuous optimization, and constrained optimization. To address the EVRP, this work proposes a hybridization of a nature-inspired metaheuristic algorithm with a greedy search component, specifically named the Genetic Algorithm

The remainder of this essay is structured as follows. In part 2, we will talk about some related research that is similar to our publication. In part 3, we also go into further detail on the mathematical perspective for EVRP. Section 4 then goes on to detail how we solved this challenge. The findings we obtained utilizing the techniques described in section 4 will then be shown in section 5. Finally, we shall have the paper's overall conclusion.

2. Related work

In recent years, the Electric Vehicle Routing Problem (EVRP) has gained significant attention due to its relevance in optimizing the operations of electric vehicle fleets. Various approaches have been proposed to tackle EVRP, ranging from heuristic methods to more advanced metaheuristic algorithms such as Genetic Algorithms (GA). In this section, we review the existing literature on EVRP and focus specifically on the utilization of heuristics and Genetic Algorithms.

2.1. Heuristic Algorithms

Several researchers have developed heuristic methods to address the Electric Vehicle Routing Problem (EVRP) and its variants, including the Capacitated Green Vehicle Routing Problem (CVRP). These methods aim to provide near-optimal solutions by relying on intuitive rules and efficient algorithms.
One notable heuristic approach specifically designed for the CVRP is the meta-heuristic proposed by Shuai Zhang et al. (2017) [3]. Their approach combines a simulated annealing algorithm with a local search procedure to tackle the capacitated routing problem with the additional consideration of green vehicles. The algorithm iteratively explores the solution space, gradually improving the initial solution through the application of neighborhood operators. The authors demonstrated the effectiveness of their approach by conducting extensive experiments on benchmark instances, showing competitive results in terms of solution quality and computational efficiency.

2.2. Genetic Algorithms

Shao S et al[4].(2017) explore a problem similar to GA, but their approach differs in terms of model formulation and optimization objectives. In [5], the authors present the first EVRP model that considers the impact of vehicle load on battery consumption. Their aim is to find an optimal routing strategy that minimizes travel time cost, energy cost, and the number of dispatched EVs. On the other hand, presents an EVRP model with charging demands, energy consumption, range constraint, and vehicle capacity constraint. The optimization goal in is to minimize the total cost, including fixed vehicle cost, travel cost, and charging cost.

To summarize the related studies, various variations of the VRP problem, including different EVRP models and proposed solution methods, have been suggested. In this paper, we propose a greedy search algorithm and a genetic algorithm as persuasive approaches to solve the EVRP problem introduced in.

3. Problem statement

The EVRP is an extension of the original NP-hard VRP problem, of which goal is to find the smallest route for all vehicles to satisfy all customers' demands, and with the constraint of starting and ending at the central depot. The additional constraint for the EVRP is that there are battery charge level limits and recharging decision-making.

The mathematical model of the EVRP is a fully connected weighted graph $G(V, A)$, where $V = U \cup R$ such that $U = \{1, ..., n\}$ is a set of n nodes (customers) in the graph, $R = \{n + 1, ..., n + s\}$ is a set of s recharging stations for EVs, set F' denotes the set of R recharging station, a central depot 0 as the starting point for all EVs, and $A = \{(i, j) \mid i, j \in N, i \neq j\}$ is a set of arcs connecting those nodes.

For every arc in the graph, it is assigned to a non-negative real value $d_{ij} \in \mathbb{R}^+$ as the Euclidean distance between two connected nodes i and j and for every node i labeled as customer has a positive demand $b_i \in U$. Besides, each EV traveling in the arc (i, j) will consume an energy amount ρd_{ij}, in which ρ is a constant denoting the consumption rate for all EVs.

Notation,parameter	Description
C	Set of customers
S	Set of charging stations
O	Depot
n_c	Number of customer
n_s	Number of charging station
n	Size of problem$(1 + n_c + n_s)$
Q_{max}	Maximum battery
P_{max}	Maximum capacity
h	Consumption rate of the EV
R_i	Route of the i-th EV
l	Number of electric vehicles
u_i	Remaining carrying capacity of an EV at node i
y_i	Remaining battery charge level of an EV at node i
b_i	Demand of customer i
	The charging station or customer visited by the vehicle in the route

The solution for the EVRP is modelized as an objective function ϕ, then our task is to find a set of routes satisfying all the customers' demand, having the minimum total traveling time, followed by the conditions as:

- EVs all start (with a full energy level and full load) and end at the central depot.
- All recharging stations should be visited multiple times on the go. (central depot included).
- Customer nodes are visited only once by one EV.
- The total demand of customers does not exceed the EV's total capacity C for every single route.
- The total energy consumption must not exceed any maximal battery charge level Q for every single route.
- EVs leave the charging station with a full battery charge level.

Mathematically, the EVRP is expressed as [1]:

$$\min \phi = \sum_{(i,j \in U \cup R) \wedge (i \neq j)} d_{ij} x_{ij} \tag{1}$$

$$\sum_{\forall i \in U \cup R, j \in V, i \neq j} x_{ij} = 1 \tag{2}$$

where two these equations respectively define the EVRP objective function and enforce the connectivity of customer visits.

$$\sum_{j \in V, i \neq j} x_{ij} \leq 1, \forall i \in F' \tag{3}$$

The third equation handles the connectivity of recharging stations.

$$\sum_{j \in V, i \neq j} x_{ij} - \sum_{j \in V, i \neq j} x_{ji} = 0, \forall i \in V \tag{4}$$

Equation (4) establishes flow conservation, i.e., by assuring that for every node, the number of incoming arcs is equal to the number of outgoing ones.

$$u_j \leq u_i - b_i x_{ij} + C\left(1 - x_{ij}\right), \forall i \in V, \forall j \in V, i \neq j \tag{5}$$

$$0 \leq u_i \leq C, \forall i \in V \tag{6}$$

s.t. variables u_i denote the remaining carrying capacity of an EV on its arrival at node $i \in V$. Equations (5) and (6) are to assure all customers' demands are all fulfilled via a non-negative carrying load upon arrival at any node (the depot included).

$$y_j \leq y_i - \rho d_{ij} x_{ij}, \forall i \in I, \forall j \in V, i \neq j \tag{7}$$

$$y_j \leq Q - \rho d_{ij} x_{ij}, \forall i \in F' \cup \{0\}, \forall j \in V, i \neq j \tag{8}$$

$$0 \leq y_i \leq Q, \forall i \in V \tag{9}$$

where variable y_i denotes the remaining battery charge level of an EV on its arrival at node $i \in V$. The condition that the battery charge never falls below 0 is guaranteed by equations (7), (8) and (9).

$$x_{ij} \in \{0, 1\}, \forall i \in V, \forall j \in V, i \neq j \tag{10}$$

The last equation defines a set of binary decision variables to recognized whether an arc is traveled or not valued by 1 and 0 respectively.

4. Methods

In this paper, we will explore and compare these two methods, heuristic and genetic, to solve the Electric Vehicle Routing Problem. By examining their strengths, weaknesses, and performance characteristics, we aim to provide insights into their suitability for different EVRP scenarios and help guide practitioners and researchers in selecting the most appropriate approach for their specific needs.c.

4.1. Heuristic Algorithms

The creation of a valid EVRP solution involves two phases: initial construction and repair procedure. Initially, the solution is built by starting at the depot and sequentially visiting each client, without considering capacity or battery level restrictions. During this phase, the Nearest Neighbor (NN) algorithm is employed to construct the solution.

Subsequently, in order to establish a valid EVRP solution, the load constraint is examined in a sequential manner. Whenever the demand of the next customer cannot be fulfilled, a depot is inserted before that customer. This approach guarantees that the load constraint is consistently met.

Variable Neighborhood Search (VNS) is a widely employed meta-heuristic technique for obtaining sub-optimal solutions to optimization problems like the Vehicle Routing Problem (VRP). It follows a systematic approach by altering the explored neighborhood in two distinct phases. First, an exhaustive local search is conducted to reach a local optimum, and then a perturbation phase is employed to escape from the corresponding valley.

Local Search: Local search is a commonly used method for solving combinatorial optimization problems. It is based on the concept that by making small modifications, known as moves, to an initial solution, it is possible to iteratively improve the solution quality. The local search approach relies on a local search operator, which defines the type of move to be performed and generates a neighborhood of solutions based on the current solution. The goal is to find high-quality solutions by exploring and improving within this neighborhood. The concept behind 2-opt is to modify a given route by removing two edges and replacing them with two new edges. This technique takes an input of a pair of indices, i and j, along with a tour T. It then returns a modified tour, T', where the sequence of nodes between indices i and j is reversed. It is a requirement that i is less than j, i is greater than or equal to 1, and j is less than n. The cost update function can be evaluated as:

$$p_{2-op} = w_{i-1,i} + w_{j+1,j} - wi - 1, j - wi, j + 1 \tag{11}$$

where the indices are expressed with respect to the tour T

4.2. Genetic Algorithms

The approach used in this study draws inspiration from Zhenfeng et al. (2017) [6]. Given that the Electric Vehicle Routing Problem (EVRP) involves complex constraints and is classified as NP-hard, finding an exact optimal solution is not straightforward. Therefore, the objective is to approximate the solution as closely to optimal as feasible. In this paper, a potential method for resolving the EVRP—the genetic algorithm—is proposed.

GA's procedure is divided into 5 separate steps, which are:

Clustering method/Initialization:In this research paper, we propose a clustering method for initialization in order to optimize the vehicle routing problem. Our approach involves a combination of generating clusters evenly and randomly. The method consists of the following steps: Firstly, a customer is randomly selected and assigned as a seed point. Secondly, a list containing customer indices from 1 to the total number of customers is created, shuffled, and distributed among the vehicles either randomly or by evenly dividing and allocating customers. Subsequently, a new list is created to store each vehicle's route as a separate list. To ensure diversity in the population, we utilize 80% of the population through a random method and allocate the remaining 20% evenly. This approach aims to enhance the efficiency and effectiveness of vehicle routing algorithms by achieving balanced and diverse initial clusters.

Evaluation: In this paper, we will use fitness value $f(i) = \sum_{(i,j \in U \cup R) \wedge (i \neq j)} d_{ij} x_{ij}$. The smaller our fitness value, the better our solution quality. On the contrary,the fitness value is invalid when $f(i) = \infty$. An invalid solution is when the constraint of the EVs' capacity or the EVs' energy capacity is violated. However, we realized that violating the EVs' capacity constraint is much worse than violating the energy one. This is because we can fix the energy capacity constraint by improving our simple repair function for charging stations placement, but in other hands, capacity violating makes our solution meaningless.

Simple Repair: the general idea of this part is to repair a given route by ensuring that a vehicle has enough energy to reach a charging station from each node. It calculates the remaining energy after departing from the first node and iterates through the route, checking if there is enough energy to reach the nearest charging station from each node. If there is insufficient energy, the function attempts to find reachable stations from the current node.If no reachable stations are found, it inserts a charging station before the current node in the repaired route. Once all nodes have been processed, the function checks if there is enough energy remaining to return back to the depot.

Local Search: After dividing the customers into distinct clusters, the local intersecting paths. The detail of the local search is described in Algorithm 1.

Algorithm 1 Local Search 2-optimal.

Input: a route in a solution with l and r are the position of the first and the last customer in the route
Output: a better route
$stop \leftarrow false$
while not stop **do**
  $stop \leftarrow true$
  for $i \leftarrow l$ to r **do**
    for $j \leftarrow r-1$ downto $i+1$ **do**
      if the total length is better than before **then**
        Swap the targets;
        $stop \leftarrow false$
        Check the energy constraint by using simple repair function

In general, this strategy will solve the EVRP problem with several advantages, such as: - Changing customers of an EV along a route does not exceed the EV's energy. This approach therefore guarantees that a solution is appropriate for energy constraint. - Due to the likelihood that clients traveling the same route would be close to one another, each option delivered by local search has an advantage in terms of total distance.

Selection: The overall idea of this method is to be selecting individuals for the next generation of the genetic algorithm. It starts by selecting a set of top-performing individuals (elites) based on their fitness scores. It then create the elites list for easier operation and repairation. After that, it removes specific nodes (stations) from the routes of the elites to create a modified version of the individuals without those stations. Finally, it fills up the remaining population slots with a portion(70%) of individuals using cross-over technique.

Cross-over: In figure 1, we show the partially-mapped crossover from Ben Desjardins et al[7], which is the method that we utilized in our paper

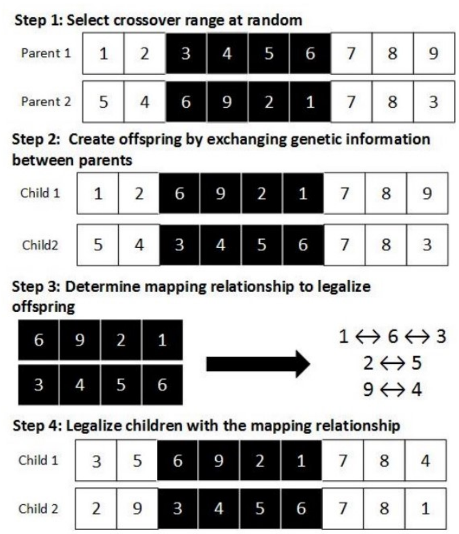

Figure 1: Example of partially-mapped crossover

5. Experimental Results

This section is to show the result of the EVRP when applying heuristic and genetic algorithm. Besides, we also compare our result with and the top 3 winner, which is the Vietnamese team in *CEC-12 Competition on Electric Vehicle Routing Problem*[1].

[1]https://mavrovouniotis.github.io/EVRPcompetition2020

Settings

In this work, we choose the population size as 10000 and number of generation as 200 for Genetic Algorithm.

Hence, we came into decision to restrict EVs' battery level to a range calculated by:

$$Q = Q - max\sum_{i\in V}\left(min\sum_{j\in R, i\neq j}\rho d_{ij}x_{ij}\right) \tag{12}$$

This helps us to find the feasible solution for some initial instances, but none for later instances.

Test instances

Our benchmark set for this paper comes from the *CEC-12 Competition on Electric Vehicle Routing Problem* [**?**]. Also in that dataset, the instance E-30-k3.evrp is wrong named because it has 4 vehicles

Table of results

There are 17 instances in the standard benchmark, we just show solvable ones however. There are 3 tables in total, which are heuristic algorithm results(Table 1), GA's results (Table 2) and the team top 3 in the competition's one (Table 3). Each table is demonstrated as: the first column consists of name of instances; the second, third, fourth and the last one respectively consists of mean, max, min and standard deviation results in 10 runs.

Result analysis

In our research, we evaluated the performance of both Heuristic and GA algorithms. We found that the genetic algorithm outperformed the Heuristic algorithm on maps with fewer than 30 customers. Conversely, the Heuristic algorithm yielded better results than the Genetic algorithm on maps with more than 30 customers.

Focusing on the Genetic algorithm alone, our findings revealed that on map E-n22-k4, our results were only marginally inferior to the top 3 team from Vietnam, with a difference of approximately 0.77 points. However, as we expanded our analysis to other maps, we observed a gradual decline in performance, with increasingly larger disparities in scores.

For the Heuristic algorithm, our results were slightly below those of the top 3 team from Vietnam, with a negligible margin. We consider this outcome satisfactory for our team. The visualization of an example using Heuristic Algorithm is presented in [2]

The initial initialization of routes for each vehicle emerged as a crucial factor in our study. It became evident that poor initialization impeded the Genetic Algorithm's ability to discover optimal solutions. Consequently, the Heuristic algorithm exhibited superior performance compared to our Genetic Algorithm, primarily due to its initialization approach using the Nearest Neighbor method.

[2]https://youtu.be/Q6cgmLqPUPU

Instances	mean	max	min	stdev
E-n22-k4	392.25	396.93	395.55	1.62
E-n23-k3	574.62	586.87	581.36	5.26
E-n30-k3	510.49	527.65	521.46	6.7
E-n33-k4	843.14	849.93	846.61	1.72
E-n51-k5	536.91	559.36	542.03	7.22
E-n76-k7	701.56	732.46	716.91	8.37
E-n101-k8	855.66	884.37	868.19	7.45
X-n143-k7	16932.79	17565.28	17349.77	213.02

TABLE 1: Heuristic algorithm's results

Instances	mean	max	min	stdev
E-n22-k4	385.44	419.25	410.33	7.37
E-n23-k3	528.60	632.51	620.99	9.64
E-n30-k3	586.24	604.13	598.38	4.26
E-n33-k4	891.83	916.77	911.40	4.74
E-n51-k5	603.04	629.24	624.00	4.30
E-n76-k7	819.59	829.69	827.23	2.04
E-n101-k8	1152.83	1172.24	1168.04	3.56
X-n143-k7	21975.11	22079.64	22057.47	17.58

TABLE 2: Genetic Algorithm's results

Instances	mean	max	min	stdev
E-n22-k4	384.67	384.67	384.67	0.0
E-n23-k3	571.94	571.94	571.94	0.0
E-n30-k3	509.47	509.47	509.47	0.0
E-n33-k4	844.25	846.21	845.62	0.92
E-n51-k5	529.90	553.23	542.08	8.57
E-n76-k7	697.27	730.92	717.30	9.58
E-n101-k8	852.69	887.14	872.69	9.58
X-n143-k7	16488.60	17478.86	16911.50	282.30

TABLE 3: Team top 3 in CEC-12 Competition on Electric Vehicle Routing Problem

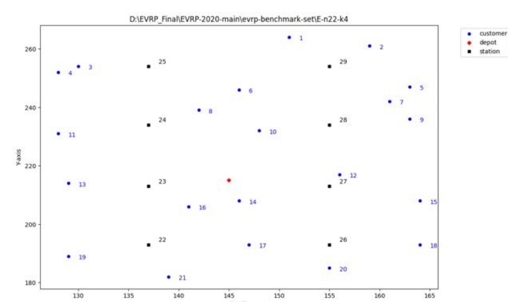

Figure 2: E-n22-k4

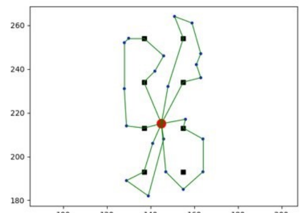

Figure 3: Heuristic Algorithm for the E-n22-k4 map

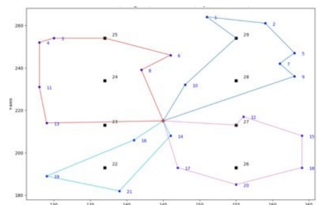

Figure 4: GA for the E-n22-k4 map

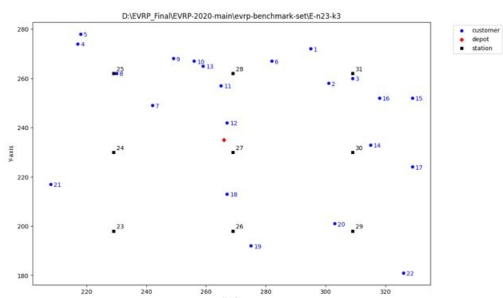

Figure 5: E-n23-k3

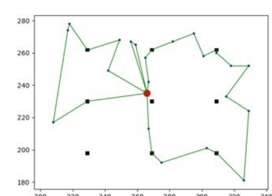

Figure 6: Heuristic Algorithm for the E-n23-k3 map

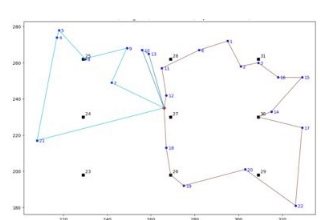

Figure 7: GA for the E-n23-k3 map

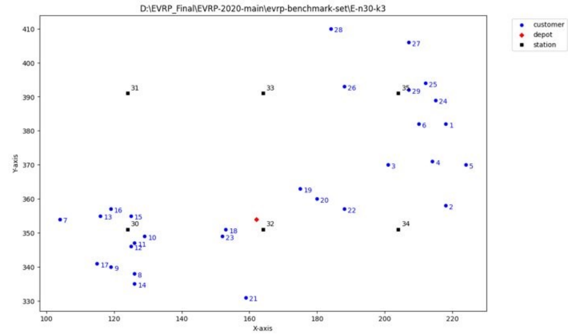

Figure 8: E-n30-k3

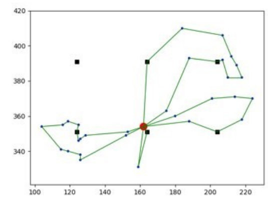

Figure 9: Heuristic Algorithm for the E-n30-k3 map

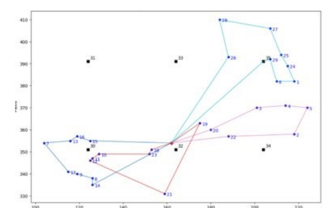

Figure 10: GA for the E-n30-k3 map

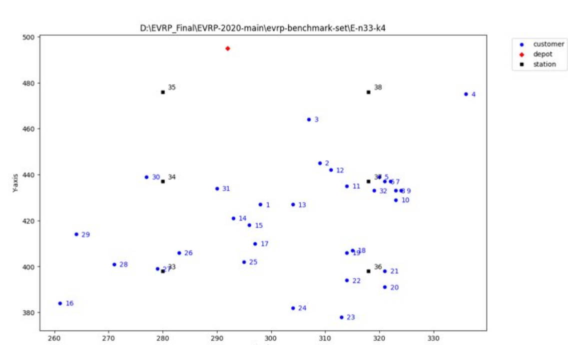

Figure 11: E-n33-k4

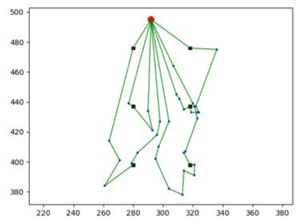

Figure 12: Heuristic Algorithm for the E-n33-k4 map

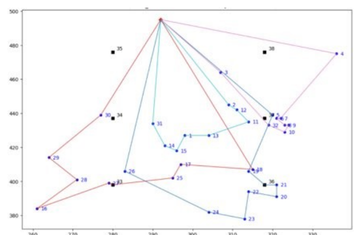

Figure 13: GA for the E-n33-k4 map

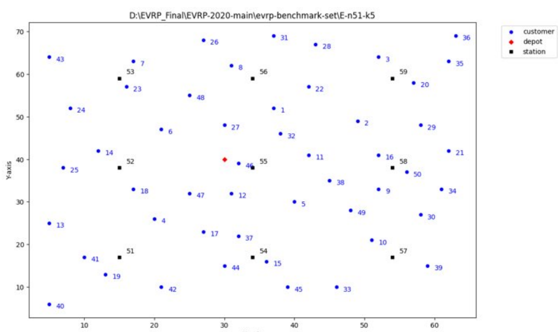

Figure 14: E-n51-k5

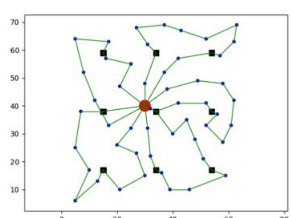

Figure 15: Heuristic Algorithm for the E-n51-k5 map

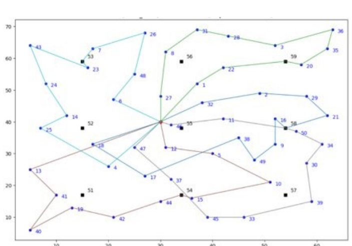

Figure 16: GA for the E-n51-k5 map

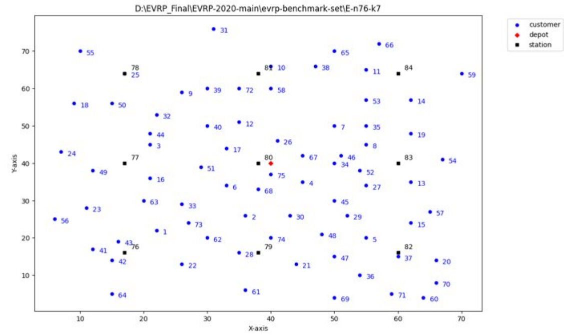

Figure 17: E-n76-k7

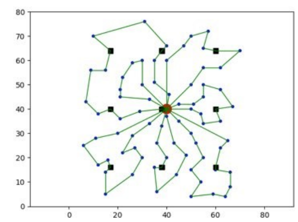

Figure 18: Heuristic Algorithm for the E-n76-k7 map

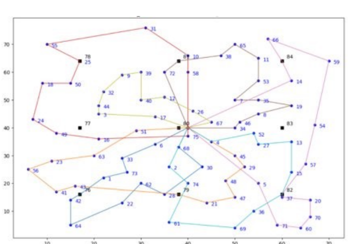

Figure 19: GA for the E-n76-k7 map

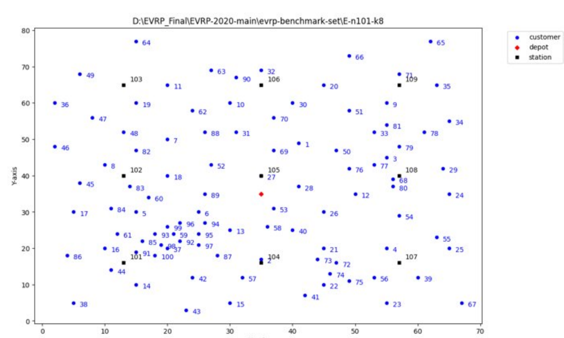

Figure 20: E-n101-k8

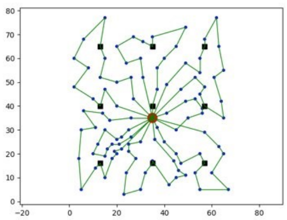

Figure 21: Heuristic Algorithm for the E-n101-k8 map

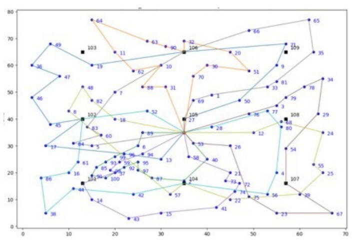

Figure 22: GA for the E-n101-k8 map

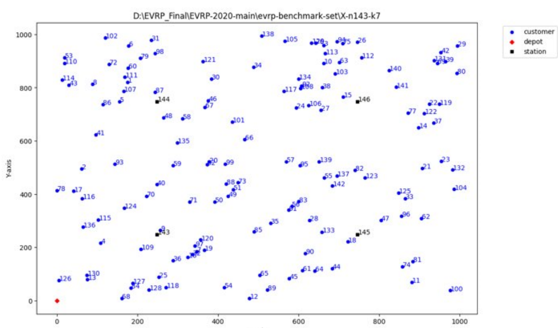

Figure 23: E-n101-k8

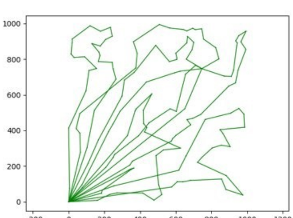

Figure 24: Heuristic Algorithm for the X-n143-k7 map

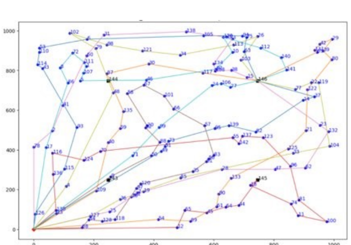

Figure 25: GA for the X-n143-k7 map

6. Conclusion

In conclusion, this comparative analysis explored two prominent methods for solving the Electric Vehicle Routing Problem (EVRP): heuristic algorithms and genetic algorithms. The EVRP poses significant challenges due to its complex nature, involving the optimization of routes for electric vehicles with limited range and the consideration of various constraints.

Heuristic algorithms, as demonstrated in this analysis, offer a practical and efficient approach to tackling the EVRP. These algorithms, such as the Clarke and Wright Savings algorithm or the Sweep algorithm, provide quick solutions by employing intuitive rules and heuristics. Although they may not always yield the globally optimal solution, they offer satisfactory results in a reasonable amount of time. Furthermore, their simplicity allows for easy implementation and adaptability to different problem instances.

On the other hand, genetic algorithms have shown their strength in addressing complex optimization problems like the EVRP. By mimicking the process of natural selection, genetic algorithms can explore a large search space and find near-optimal solutions. Through the use of genetic operators such as crossover and mutation, these algorithms maintain a diverse population of solutions and continually improve them over successive generations. However, the computational cost associated with genetic algorithms may be higher compared to heuristic algorithms, especially when dealing with large problem instances.

Both heuristic algorithms and genetic algorithms have their advantages and limitations when applied to the EVRP. Heuristic algorithms offer simplicity, efficiency, and practicality, making them suitable for solving medium-sized problem instances. Genetic algorithms, on the other hand, excel in handling larger and more complex instances by leveraging their ability to explore the search space effectively.

Ultimately, the choice between these two methods depends on the specific requirements of the EVRP, including the problem size, time constraints, and the desired level of solution quality. A hybrid approach that combines the strengths of both methods could also be considered, aiming to strike a balance between solution quality and computational efficiency.

In conclusion, this comparative analysis underscores the significance of selecting appropriate methods for solving the EVRP. The selection should be based on a careful evaluation of the problem characteristics and the trade-off between solution quality and computational resources. Both heuristic algorithms and genetic algorithms offer valuable approaches to address the EVRP, and further research and experimentation are needed to explore their potential synergies and improve their performance in solving this challenging problem.

References

[1] U. S. E. P. Agency. (2019) Carbon pollution from transportation. [Online]. Avail- able:

https://www.epa.gov/transportation-air-pollution- and-climate-change/carbon-pollution-transportation

[2] M. Mavrovouniotis, C. Menelaou, S. Timotheou, C. Panayiotou, G. Ellinas, and M. Polycarpou, “Bench- mark set for the ieee wcci-2020 competition on evo- lutionary computation for the electric vehicle routing problem,” 03 2020.

[3] Shuai Zhang, Yuvraj Gajpal, and S. S. Appadoo, A meta-heuristic for capacitated green vehicle routing problem, Annals of Operations Research 269 (2018), no. 1-2, 753–771.

[4] Shao S, Guan W, Bi J (2017) Electric vehicle-routing problem with charging demands and energy consumption. IET Intell Transp Syst 12(3):202–212

[5]. Lin J, Zhou W, Wolfson O (2016) Electric vehicle routing problem. Transp Res Procedia 12:508–521

[6] G. Zhenfeng, L. Yang, J. Xiaodan, and G. Sheng, “The electric vehicle routing problem with time windows us- ing genetic algorithm,” in 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2017, pp. 635–639.

[7] B. Desjardins, R. Falcon, R. Abielmona, and E. Petriu, ”Planning robust sensor relocation trajectories for a mobile robot with evolutionary multi-objective optimization,” in Computational Intelligence in Wireless Sensor Networks, Springer, Cham, 2017, pp. 179-210.