A Combination between Genetic Algorithm and Heuristic Algorithm in Electric Vehicle Routing Problem

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***Abstract*—Driven by the badly directing in the present environment, it is urgent to find out alternative way to reduce the greenhouse gas and using electric vehicles is by far the best choice nowadays. And solving the problem of optimizing routes for the electric vehicles or also known as the Electric Vehicle Routing Problem is considered as a needed problem to be solved. In this paper, we give out a combination between Genetic Algorithm and a simple heuristic for Charging Stations Placement to solve this problem. We divided our problem into two separate sections, which are Electric Vehicle Routing and Locations of Charging Stations.**

***Index Terms*—Electric Vehicles, K-means, Heuristics, Distance Optimizing, Genetic Algorithm, Charging Stations Placement**

1. Introduction

In present days, the market has a more tendency to compete to each other. The existence for an effective, feasible and environmental-friendly transporting system is a crucial factor of a logistic company. One of the present strategy of those companies is to shift to a newer type of vehicles: Electric Vehicles (EVs). This is understandable due to the continuously raising need for energy alternatives, which is comprehensible due to the present global warming, pollution and climate changes. The problem is such urgent that there are quite a few logistic companies around the world now establish their own campaigns to manufacture CO_2-emission reduction of daily operations, e.g. Tesla, FedEx. Among the contributing factor to environmental harm, there is no doubt that transportation is the primary component, which gives out 29% of the total greenhouse gas emission to the Earth [1]. The most effective way to reduce the greenhouse gas, hence, is to use electric vehicles (EVs).

The *vehicle routing problem* (VRP) is not a new problem, it was first introduced in 2002 [2]. The problem is demonstrated as finding the shortest routing solution for a set of vehicles to visit a set of locations satisfying customers' needs [3]. Due to the effective of the VRP, there is a wide range of variation to the original problem itself. One of the upgraded versions for VRP is known as the VRP with EVs or the *electric vehicle routing problem* (EVRP) [4], EVRP is considered as a more difficult problem in comparison with the original one due to the recharging decision-making and more complex objective function requiring to minimize distance cost [5]. EVRP is found to be quite difficult since it is relevant to distribute logistics in not only identifying customers set with a fixed demand but satisfying EVs' energy capacity also. In addition, the ultimate goal is to minimize the total distance between the EVs. And in this paper, we did make a minor change - which is discussed further in 2.1 - to the indigenous version.

Genetic algorithm (GA) [6] is a search-based technique which have been used in optimization fields for practical problems. The idea behind the algorithm itself is based on the natural selection given by Charles Darwin's evolutionary synthesis in the 1860s. The basic concept for GA can be understood as the well-performed result will still remain in the population and produce their better successor continuously, while the worse performance is removed. And the process proceeds on and on until the inappropriate individuals become extincted eventually.

The rest of this paper is organized as follows. We will discuss some of related work sharing the similarity to our paper in section 2. We also discuss further about mathematical view for EVRP in section 3. Next, section 4 describes about our methods to solve this problem. Then, section 5 will display our results in using methods in the previous section. After that, section 6 will talk more about our limitations and ways to minimize them in our future work. Finally, we will have our final conclusion for the whole paper.

2. Related work

Solving the EVRP with an effective solution is an urgent need, and it is clear to realize in the study below. Throughout this work, we solve the electric vehicle routing and location of Charging Stations (CSs) separately. The mentioned research, thus, is divided into two individual sections.

2.1. Location of charging stations

Location of CSs is a problem with multiple objective functions, e.g. energy cost and total travel distance.

Hidalgo et al. (2016) [7] proposed a GA for location of CSs considering actual demand of electric energy consumption, with different capacities and energy levels between vehicles. Dong et al. (2016) [8] proposed a two-phases solution. In the first one, they use K-means [9] to divide the market into regions based on demands. They use a model to acknowledge locations of CSs while still maximizing operational productivity in the second one.

Lam et al. (2013) [10] proposed a mathematical formulation for the problem and they provide four strategies to solve that problem, including mixed integer linear programming iterative method, greedy algorithm, mixed integer linear programming approach, chemical reaction optimization. Gatica et al. (2018) [11] also proposed four solution strategies for the location of CSs and a heuristic solution for electric vehicle routing. Comparing to other strategies, K-means gives out the best performance when locating the charging stations at the centroid of the cluster.

Zhenfeng et al. (2017) [12] proposed a effective genetic algorithm with crossover, mutation and initialization. Hence, GA's operations in this work is mostly based on the forementioned paper. This paper, however, goes through all the charging stations once only. Fazeli et al. (2021) [13] proposed an efficient branch and cut framework and a three-phase heuristic algorithm that can efficiently solve a variety of instances for min-max electric vehicle routing problem (MEVRP). They use a wide range of techniques, e.g. Variable Neighborhood Search, LKH Heuristic, Genetic Algorithm.

Almost recent studies show the advance in researching for this problem. Late trends are to propose modelizing the problem into mathematical formulas, as well as differently problem-approaching strategies. And among those highlighted K-means strategy, which seems to be quite simple but highly effective.

2.2. Electric vehicle routing

At the beginning, the Electric Vehicle Routing problem was invariant and far different from what we know nowadays [14].

The vehicle routing problem was first laid the ground by Dantzig and Ramser in 1959 [15]; they showed the explanation for the problem of assigning stations for vehicles to travel between two any given points in the shortest way and satisfy all the customers' demands. And five years later, the problem was formalised and mathematically demonstrated for both computer solving and human solving by Clarke and Wright in 1964 [16].

Braekers et al. (2015) [17] showed the importance and potential for the vehicle routing problem in our present 21^{st} days by manifesting its variants and differently approaching techniques from 2009 to 2015; and Metaheuristic algorithms by far outweighed the others. There, one of the most investigated variants for the VRP was the EVRP due to the need for cost reducing and protecting the environment in the industry. The solution for the problem was also first proposed as in Braekers et al. after considering several restrictions.

The exact problem of the EVRP with recharging stations and an exact method was first introduced by Conrad and Figliozzi (2011) [18]. In this work, the author gave a exact demonstration for a sub-problem in the present EVRP nowadays of which EVs are enabled to recharging battery after traveling at customers nodes. In later times, Erdogan and Miller-Hooks (2012) [19] proposed two construction heuristics, which are the Modified Clarke - Wright Savings heuristic and the Density-Based Clustering Algorithm, was shown to work efficiently on the problem of Green Vehicle Routing Problem (GVRP). Anagnostopoulou et al. (2014) [20] proposed a mathematical formulation to modelize multiple constraints in the Electric Vehicle Routing Problem with Time Windows (EVRP-TW).

Reviewing these proposals and approaching point to solve the EVRP, we might consider to use heuristics and metaheuristics instead of exact strategies. This is comprehensible due to the unpredictable customers' demands and too many constraints for an exact efficient solution strategy to handle.

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.

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 [21]:

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

s.t.

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

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

This method is inspired by Zhenfeng et al. (2017) [22]. Since the Electric Vehicle Routing Problem is a NP-hard problem with sophisticated constraints, there is no obvious optimal solution to the problem itself, thus we have to approximate the solution as optimal as possible. In this paper, Genetic Algorithm is proposed as a promising solution to solve the EVRP.

The problem is encoded in such a way that the depot (0), customer nodes (1,...,n) and recharging stations (n + 1, n + 2,...,n +m) are encoded by a natural number, and the gene values are put into order of visiting sequence [22]. Figure 1 demonstrates the way three routes of 3 EVs are encoded into a chromosome: EV 1 starts from the depot 0 and visits customer node 5 and 3 and returns to the depot after recharging at recharging nodes 6 and visits customer node 7; EV 2 from the depot travels to customer node 8 and recharges at recharging node 9, then it visits customer node 2 and returns to the depot; EV 3 starts from the depot, visits customer nodes 4, 1 and 10 and returns to the depot without a need to recharge.

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

Figure 1: Chromosome representation of a problem

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

Initialization: In this step, we randomly assign the code number for customer nodes in the genes, but we do not execute the same thing for Recharging Stations. In order to generate a better population, we use *K-means* [9] to initialize chromosomes (individual): we choose k = number of EV in the problem, and for every gene in our population, we will choose a different random seed to guarantee the diversity of the original population. We have to ensure that the population involves N individuals, s.t. N = number of customers + number of EV + 1, the initialization satisfy the customer needs for each node and never do an EV exceed the loading capacity Q as well.
Let denote q'_i as the customer node's demand. We shall

add number 0 after the t gene in the chromosome if $\sum_{i=1}^{t} q_i' \leq Q$ and $\sum_{i=1}^{t+1} q_i' < Q$. We will repeatedly execute this number 0 insertion $n-1$ times in both first and last gene respectively.

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 heuristic function for charging stations placement, but in other hands, capacity violating makes our solution meaningless.

Selection: In this problem, we choose the *Tournament Selection* [23] as the key. Tournament Selection is a method to choose an individual from a population of individuals in a Genetic Algorithm. It consists of several tournaments between a few randomly chosen individuals from the population. The winner (individual with the best fitness) in each tournament is selected to proceed the crossover process.

Heuristic function to add recharging stations: We create an energy list e, in which e_i is the distance from node i to the nearest charging station, at the beginning. Then, we will loop through each element i in the population's individual, if the sum of total energy consumption from beginning to node i and sufficient energy to get to the next node (node $i+1$) is larger than Q subtracted by e_{i+1}, after that we will add the charging stations between node i and node $i+1$ via Dijkstra algorithm [24], in which the starting point is node i, the ending point is node $i+1$ and the rest in graph is charging stations. We only add the edges between two vertices into graph if energy cost of those does not exceed the EV's remaining energy.
The result of Dijkstra algorithm is a list of charging stations and we will add these nodes into between node i and $i+1$ in this individual.

Crossover: We realized that keeping charging stations in individuals will make the problem more difficult when individual's size is not the same in the population. Furthermore, recharging stations do not play an important role when it comes to crossover process. We will get rid of all existing recharging stations from the whole population in this step, thus.
The crossover procedure consists of 6 sub-steps:

1) Remove all recharging stations in the population.
2) Randomly choose a segment of genes in the chromosome.
3) Move the selected sub-path in each parent to the front genes in the chromosome.

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

Figure 2: Randomly choose the sub-solution in parents 1

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

Figure 3: Randomly choose the sub-solution in parents 2

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

Figure 4: Change the sub-solution in parents 1 to the front

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

Figure 5: Change the sub-solution in parents 2 to the front

4) Keep sub-path of the first chromosome in offspring 1, add the genes of the second chromosome which the first chromosome does not include after sub-path as their sequence. Add number 0 in the last gene of chromosome.

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

Figure 6: Offspring 1

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

Figure 7: Offspring 2

5) Add number 0 in any gene after the first sub-path and select the offspring with the highest value of fitness. The second offspring is obtained in the same manner.

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

Figure 8: Add number 0 to any genes randomly

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

Figure 9: Add number 0 to any genes randomly

6) Add recharging stations to every chromosome in the population.

Mutation: Although GA requires mutation step, we do not use this step in our paper.

Terminated criterion: We will stop the procedure once the number of iteration exceeds the maximum value or our population converges, which means all the individuals are perfectly identical. Or else, if both conditions are not satisfied, we will return and continue the above process.

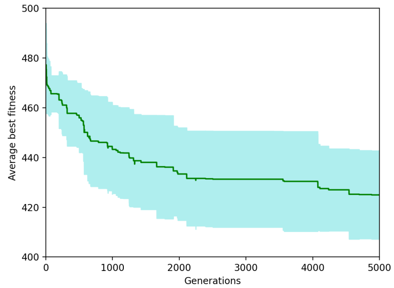

Figure 10: E-n22-k4

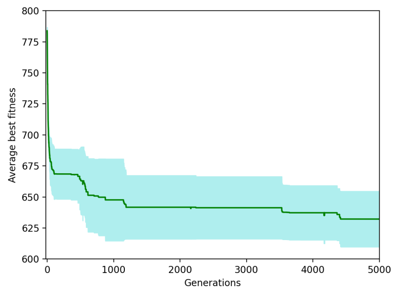

Figure 11: E-n23-k3

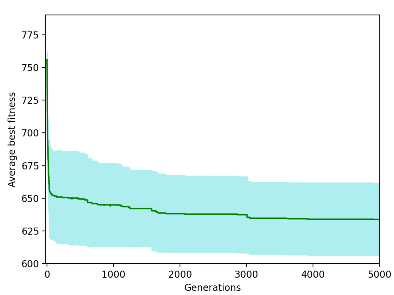

Figure 12: E-n30-k3

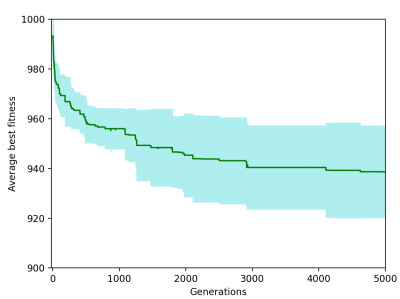

Figure 13: E-n33-k4

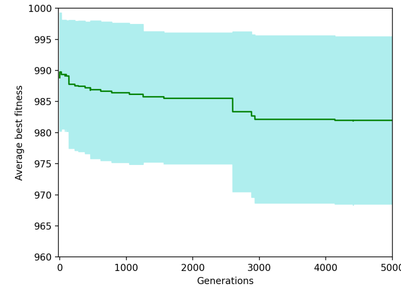

Figure 14: E-n51-k5

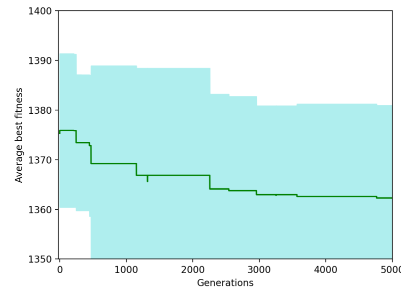

Figure 15: E-n76-k7

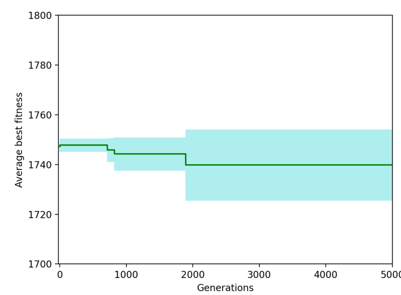

Figure 16: E-n101-k8

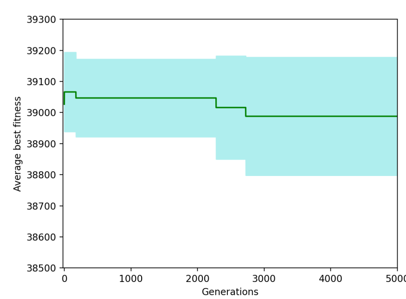

Figure 17: X-n143-k7

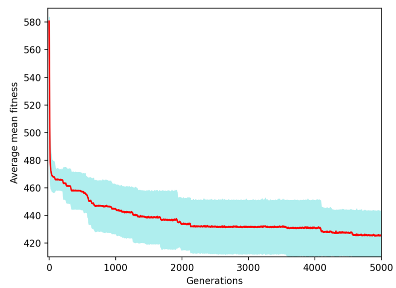

Figure 18: E-n22-k4

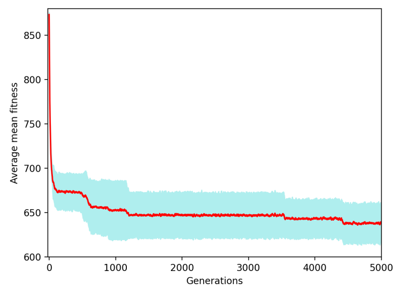

Figure 19: E-n23-k3

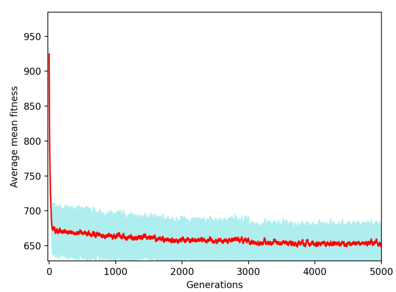

Figure 20: E-n30-k3

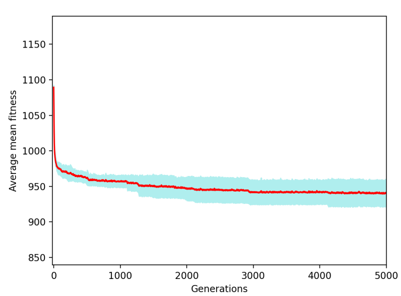

Figure 21: E-n33-k4

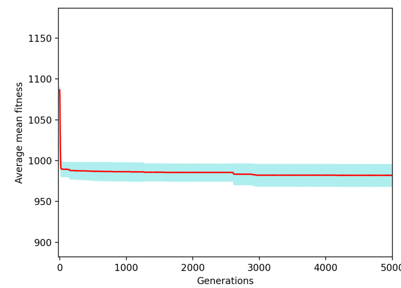

Figure 22: E-n51-k5

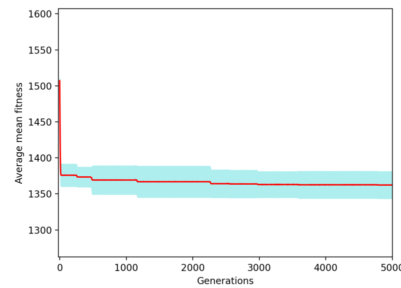

Figure 23: E-n76-k7

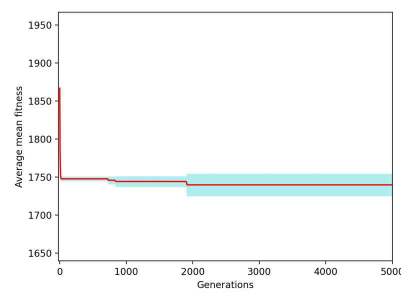

Figure 24: E-n101-k8

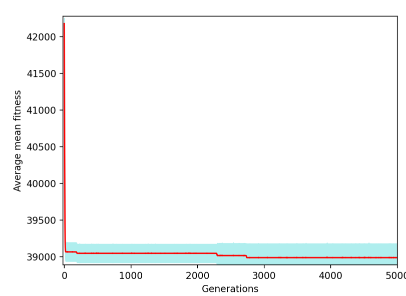

Figure 25: X-n143-k7

In addition to Genetic Algorithm, we also propose *Google OR-Tools* [25] to handle the EVRP. Google OR-Tools provides us a tool to handle combinatorial optimization problem (C.O.P) via an open-source software. This tool can help us to find the best (or relatively good) solution for our present problem through a large set of possible feasible solutions.

In the vehicle routing problem, Google OR-Tools is designed to find the optimal routes as the solution, and OR-Tools defines an optimal route as the route with the smallest total distance and all constraints are satisfied [3]. Since OR-Tools has not introduced an obvious tool to solve the EVRP but the VRP only, we shall demonstrate our approach to make OR-Tools able to solve this problem effectively.

5. Results

This section is to show the result of the EVRP when applying GA. Besides, we also compare our result with Google OR-Tools and the winner in *CEC-12 Competition on Electric Vehicle Routing Problem*[1].

Settings

In this work, we choose the population size as 400 and number of generation as 5000 for Genetic Algorithm.

Google OR-Tools is a restricted framework and there is few documents to reference which leads to many a difficulty when applying this framework into solving the EVRP. When applying OR-Tools to solve this problem, we got into trouble which is EVs forgot to pay energy cost while moving to another recharging stations but still got fully recharged. This unfortunately leads to the OR-Tools can not give any appropriate solutions.

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

$$Q = Q - max \sum_{i \in V} \left(min \sum_{j \in R, i \neq j} \rho d_{ij} x_{ij} \right) \tag{11}$$

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* [21].

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 GA's results (Table 1), Google OR-Tools' results (Table 2) and the winner team 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.
We also give out 8 plots responding to 8 first instances solve by GA. The x-axis stands for number of generations and the y-axis is the average best fitness in 10 runs. The pale turquoise zone represents for the standard deviation.

Result analysis

Incomplete as Google OR-Tools is, it still gives out the solution for the first five instances, in which the results for E-n22-k4 and E-n51-k5 is excellent; the results are even better than our GA's and quite close to the winner team's results.

Our GA's result in Table 3 is outstanding with n ¡ 50 and it is quite close to the winner team's results. It becomes worse or even unsolvable, however, when n $>$ 50 and n $>$ 200, respectively.

When observing plots, it is clear that K-means helps Genetic algorithm to generate a relatively good population. This can be shown since the green line has a tendency to decrease, which is a good signal. Thus, if we increase number of generations, that green line has a probability to go shallower. However, crossover as soon as the loop starts makes GA unable to keep good individuals in the generating step. This is the reason for green line goes up when starting and go downhill when the numbers of generation increase in some plot.

Instances	mean	max	min	stdev
E-n22-k4	401	401	401	0
E-n23-k3	701	701	701	0
E-n30-k3	635.4	644	603	11.7149
E-n33-k4	997.8	1012	967	19.3845
E-n51-k5	606.8	624	572	14.4069

TABLE 1: Google OR-Tools' results

Instances	mean	max	min	stdev
E-n22-k4	384.67	384.67	384.67	0
E-n23-k3	571.94	571.94	571.94	0
E-n30-k3	509.47	509.47	509.47	0
E-n33-k4	840.14	840.46	840.43	1.18
E-n51-k5	529.90	548.98	543.26	3.52
E-n76-k7	692.94	707.49	697.89	3.09
E-n101-k8	839.29	853.34	853.34	4.73
X-n143-k7	16028.05	16883.38	16459.31	242.59

TABLE 2: Variable Neighborhood Search's results by D. Woller, V. Vavra, V. Kozak, M. Kulich

6. Future work

In this paper, due to the time pressure, we did not do the mutation. However, we do believe that mutation step is

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

Instances	mean	max	min	stdev
E-n22-k4	424.95	464.39	402.53	18.7183
E-n23-k3	632.19	671.62	607.01	23.5857
E-n30-k3	633.81	669.65	593.78	29.0584
E-n33-k4	938.66	959.64	898.62	19.4428
E-n51-k5	981.97	1004.74	961.03	14.1877
E-n76-k7	1362.30	1391.84	1323.60	19.6518
E-n101-k8	1739.82	1752.73	1702.07	14.9056
X-n143-k7	38987.96	39384.5	38683.4	200.2779

TABLE 3: Genetic Algorithm's results

a crucial factor in GA and it might increase the quality of our solution. We will research it more in the future.

We also research a better heuristic function for locating recharging stations compared to our present one. This is due to the fact that adding recharging stations based on the energy cost from the next node to the nearest recharging station of that node is not good at all. We could choose a further recharging station sharing the same direction to the solution's trajectory, as long as going to that recharging station does not exhaust the whole remaining energy level.

Besides, we would also research more efficient crossover methods. We just solve the EVRP with the problem size of less than 200 in present, the population with a larger than 200 problems size is unacceptable poor since there is no feasible solution in the indigenous population. Thus, we will also find a more effective way to initialize the starting population as good as possible to solve large-scale problems and improve the smaller-problem size solution.

7. Conclusion

In this work, we consider the Electric Vehicle Routing Problem. We did propose a potential solution with several techniques, e.g. Genetic Algorithm, Dijkstra, K-means and some heuristics.

Separating a big problem into two smaller ones, which are electric vehicle routing and locations of charging stations, enables us inheriting results from previous researches in GA for the VRP. Then, we could design an additional heuristic to add recharging stations into chromosomes to solve the EVRP.

However, heuristics seem to be insufficient despite sustaining feasible at least one solution. Furthermore, generating a not so well population prevents GA from finding any solution. Thus, beside the proposed solution - which is K-means, we would find newer methods.

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Biography

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An Vo graduated in 2019 at Phan Ngoc Hien High school for the gifted, Ca Mau province, specified for Mathematics - Informatics. From 2019, he has been studying at University of Information Technology, Vietnam National University HCMC, faculty of Computer Science, class of KHCL2019.1.

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References

[1] U. S. E. P. Agency. (2019) Carbon pollution from transportation. [Online]. Available: https://www.epa.gov/transportation-air-pollution-and-climate-change/carbon-pollution-transportation

[2] P. Toth and D. Vigo, *The vehicle routing problem*. SIAM, 2002.
[3] "Vehicle routing problem," Google, 2019. [Online]. Available: https://developers.google.com/optimization/routing/vrp
[4] J. Lin, W. Zhou, and O. Wolfson, "Electric vehicle routing problem," *Transportation Research Procedia*, vol. 12, pp. 508–521, 2016, tenth International Conference on City Logistics 17-19 June 2015, Tenerife, Spain.
[5] A. Ceselli, Felipe, M. T. Ortuño, G. Righini, and G. Tirado, "A branch-and-cut-and-price algorithm for the electric vehicle routing problem with multiple technologies," *SN Operations Research Forum*, vol. 2, no. 1, pp. 1–33, 2021. [Online]. Available: https://doi.org/10.1007/s43069-020-00052-x
[6] M. Mitchell, *An Introduction to Genetic Algorithms*. Cambridge, MA, USA: MIT Press, 1998.
[7] P. A. L. Hidalgo, M. Ostendorp, and M. Lienkamp, "Optimizing the charging station placement by considering the user's charging behavior," in *2016 IEEE International Energy Conference (ENERGYCON)*, 2016, pp. 1–7.
[8] Y. Dong, S. Qian, J. Liu, L. Zhang, and K. Zhang, "Optimal placement of charging stations for electric taxis in urban area with profit maximization," in *2016 17th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, 2016, pp. 177–182.
[9] X. Jin and J. Han, *K-Means Clustering*, C. Sammut and G. I. Webb, Eds. Boston, MA: Springer US, 2010. [Online]. Available: https://doi.org/10.1007/978-0-387-30164-8_425
[10] A. Y. Lam, Y.-W. Leung, and X. Chu, "Electric vehicle charging station placement," in *2013 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2013, pp. 510–515.
[11] G. Gatica, G. AHUMADA, J. Escobar, and R. LINFATI, "Efficient heuristic algorithms for location of charging stations in electric vehicle routing problems," *Studies in Informatics and Control*, vol. 27, 03 2018.
[12] G. Zhenfeng, L. Yang, J. Xiaodan, and G. Sheng, "The electric vehicle routing problem with time windows using genetic algorithm," in *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2017, pp. 635–639.
[13] S. S. Fazeli, S. Venkatachalam, and J. M. Smereka, "Efficient algorithms for electric vehicles' min-max routing problem," 2021.
[14] G. Gatica, G. AHUMADA, J. Escobar, and R. LINFATI, "Efficient heuristic algorithms for location of charging stations in electric vehicle routing problems," *Studies in Informatics and Control*, vol. 27, 03 2018.
[15] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Manage. Sci.*, vol. 6, no. 1, p. 80–91, Oct. 1959. [Online]. Available: https://doi.org/10.1287/mnsc.6.1.80
[16] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Oper. Res.*, vol. 12, no. 4, p. 568–581, Aug. 1964. [Online]. Available: https://doi.org/10.1287/opre.12.4.568
[17] K. Braekers, K. Ramaekers, and I. Nieuwenhuyse, "The vehicle routing problem: State of the art classification and review," *Computers Industrial Engineering*, vol. 99, 12 2015.
[18] R. Conrad and M. Figliozzi, "The recharging vehicle routing problem," *Proc. of the 61st Annual IIE Conference*, 01 2011.
[19] S. Erdogan and E. Miller-Hooks, "A green vehicle routing problem," *Transportation Research Part E: Logistics and Transportation Review*, vol. 109, p. 100–114, 01 2012.
[20] A. Anagnostopoulou, M. Boile, S. Theofanis, E. Sdoukopoulos, and D. Margaritis, "Electric vehicle routing problem with industry constraints: Trends and insights for future research," *Transportation Research Procedia*, vol. 3, p. 452 – 459, 07 2014.
[21] M. Mavrovouniotis, C. Menelaou, S. Timotheou, C. Panayiotou, G. Ellinas, and M. Polycarpou, "Benchmark set for the ieee wcci-2020 competition on evolutionary computation for the electric vehicle routing problem," 03 2020.
[22] G. Zhenfeng, L. Yang, J. Xiaodan, and G. Sheng, "The electric vehicle routing problem with time windows using genetic algorithm," in *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2017, pp. 635–639.
[23] B. L. Miller and D. Goldberg, "Genetic algorithms, tournament selection, and the effects of noise," *Complex Syst.*, vol. 9, 1995.
[24] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische mathematik*, vol. 1, no. 1, pp. 269–271, 1959.
[25] L. Perron and V. Furnon, "Or-tools," Google. [Online]. Available: https://developers.google.com/optimization/