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ELECTRIC VEHICLE ROUTING PROBLEM USING ADAPTIVE SIMULATED ANNEALING

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Abstract Road transport is a major CO_2 emission contributor globally. To tackle the challenge of reducing world carbon emissions, alternative technologies for the automobile industry are widely researched. The automotive industry has started to shift from Internal combustion engine (ICE) vehicles to electric vehicles (EVs), where EVs are the future of the automotive industry in terms of reducing greenhouse gas emissions and air pollution. EV manufacturers are continuously looking for opportunities to optimize the supply chain processes, aiming for supply chain resilience. In this study, we present an Electric Vehicle Routing Problem (EVRP) to achieve the best decision, which is an extension of the traditional Vehicle routing problem (VRP) which in particular finding the shortest route for electric vehicles. The objective function is to find the best travel route that minimizes travel distance. Each route serves a set of customer nodes that starts and ends at a given depot node. We take battery capacity and charging stations as the constraints. In addition, the use of homogenous fleets and single depot are considered in this paper. A hybrid metaheuristic approach is used to find the best solution with the Adaptive Simulated Annealing algorithm. The use of adaptive in simulated annealing generates a higher probability of finding the best operators, which results in better solutions. A comparison of results from various metaheuristic methods is also presented in this paper to get the best method for the EVRP based on a benchmark dataset. This paper ends with recommendations for creating a routing plan that is resilient to disruptions to distribution.

Keywords: Electric Vehicle Routing Problem; Adaptive Simulated Annealing; Metaheuristic

1. Introduction

The current industry development is becoming more conscious of the topic of sustainability. One of the main goals is to reduce carbon gas emissions and protect nature from adverse impacts. Not only manufacturing activities that focus on reducing factory waste by implementing effective waste management, but also distribution and transportation activities have begun to shift towards green regulations. The adoption of zero-emission electric vehicles (EVs) is today's ambitious goal for global transportation decarbonization, particularly in industrialized nations that see the critical need for sustainable transportation solutions (Erdogan et al., 2022). As part of its push to decrease carbon emissions, the European Union (EU) has unveiled a determined plan to ban the sale of new gasoline and diesel vehicles beginning in 2035. The EU has set an ambitious aim of reducing CO2 emissions from automobiles by 55% by 2030 compared to 2021[1].

The use of electric vehicles to support business processes reflects that business actors have taken a part in preserving the environment by reducing the effects of pollution, compared to combustion vehicles. In addition to aiming for sustainability, the use of electric-based vehicles is promising to reduce total transportation costs. Therefore, to support business activities in each chain, many freight activities are starting to be carried out using electric vehicles. If compared to the use of gas as fuel, charging power is believed to be much cheaper than the cost of gas per liter. However, the limitation faced by EV users is the lack of facilities to support the operation of this emerging technology.

Recharging the EVs has more critical issues than refueling of conventional vehicle that

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using fossil fuel because the limited availability of charging facilities, limited cruising range, and long charging times[2]. For example, every delivery needs to select the best route by considering the existing charging facilities and the power capacity of the vehicle. This scenario is certainly different when compared to a combustion vehicle, which can more easily find a refueling point every travel. In this study, the determination of travel routes using electric-based vehicles will be conducted.

We will determine the best travel route using electric vehicles, known as the electric vehicle routing problem (EVRP). EVRP is an extension of the traditional vehicle routing problem (VRP) which in particular finding best travel routes for electric vehicles that have constraints of battery and charging operations [3]. The objective function is to find the best route plan that minimizes travel distance. Each route serves a set of customer nodes that starts and ends at a given depot node. We take battery capacity and charging stations as the constraints. In addition, the use of homogenous fleets and single depot are considered in this paper. Initially, precise approaches like the Branch and Bound algorithm proved effective in addressing VRP instances involving fewer than 25 customers and remained under development until the number of customers reached less than 50 [4]. However, as VRP evolved over time, it became increasingly challenging with larger scales, demanding swift resolutions. Consequently, exact algorithms only remained efficient for smaller problem instances. Metaheuristics, unlike brute force approaches or exact solution, offer faster computation by providing approximate solutions that are close to optimal [5]. This stark contrast to conventional methods enables the calculation process to be expedited while still yielding satisfactory results. To overcome the limitations of precise algorithms in terms of time efficiency, heuristics and metaheuristics emerged as viable alternatives for solving VRP cases promptly. A hybrid metaheuristic approach is used to find the best solution with Adaptive Simulated Annealing. The use of adaptive in simulated annealing generates a higher probability of finding the best operators, which results in better solutions. A comparison of results from various metaheuristic methods is also presented in this paper to get the best method for the EVRP based on a given dataset.

2. Literature review

We briefly explain the recent relevant works on the electric vehicle routing problem and Adaptive Simulated Annealing.

2.1. Electric Vehicle Routing Problem

EVRP is a problem for determining the route of electric vehicles that depart from the depot, visit several customers, and return to the depot. The purpose of the EVRP is to minimize the total mileage with the limitations of vehicle capacity, battery capacity, and other limitations[3].

a. For each route, vehicles depart from the depot and end up at the same depot.
b. Each customer is visited only once by one electric vehicle.
c. Electric vehicles can visit charging stations between 2 customers to charge the battery.
d. Each charging station can be visited by one or more electric vehicles.
e. The distance from each customer to each charging station is known.
f. EVs battery level must be more than 0 and not more than its battery capacity.
g. Vehicles that have visited the charging station make the battery level always full.

Similar studies have been conducted to solve Electric Vehicle Routing Problem (EVRP) using a metaheuristic with each constraint and objective function. The VRP containing alternative fuel vehicles, an alternative to EV and named a green vehicle routing problem (GVRP)[6]. In the GVRP, a limited fuel capacity of vehicles and the possibility of refueling at alternative fuel stations (AFSs) during its tour are considered. The objective is to minimize the total traveled distance among customers. Later studies have done with different variations using some realistic constraints such as a time window of customers, using different recharge technologies, and allowing partial recharges[7]–[9]. The latest study considered the multi-objectivity concept of the electric vehicle routing problem that are three multi-objective electric vehicle routing problems (MOEVRPs) considering different realistic constraints[10]. These problems differ in terms of the charging strategies (full or partial) of the EVs and the charger types (slow, medium, or fast), namely multi-objective electric vehicle routing problem (MOEVRP), multi-objective electric vehicle

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routing problem with partial recharges (MOEVRP-PR), and multi-objective electric vehicle routing problem with multiple technologies and partial recharges (MOEVRP-MTPR).

The Electric Vehiclre Routing Problem with Time Windows was introduced by the seminal work, where the problem is formulated as a Mixed Integer Linear Programming on a complete direct graph, in which the set of vertices includes the depot, the customers and the clones of the RSs possibly visited en-route by the EVs for full recharges[7]. Indeed, to allow using each RS more than once in the same route and/or solution, some copies of it are introduced.

Besides, studies about the time-effective Electric Vehicle Routing Problem with Time Windows (E-VRPTS) in [11] E-VRPTW is addressed in [12] through a three-steps matheuristic able to outperform a Variable Neighborhood Search (VNS) based especially on medium-sized instances. Then, model E-VRPTW as a Mixed Integer Linear Program (MILP) where the speeds of vehicles are continuous variables that can vary between a minimum and a maximum value[13]. To efficiently solve large-sized instances of the problem, they designed a Random Kernel Search (RKS) matheuristic approach, based on the cloneless MILP formulation, that in turn exploits another matheuristic, called Random k-Degree Search (RkDS), to generate an initial feasible solution. The effectiveness of RKS was confirmed by the results obtained for both the sets. Indeed, RKS was able to improve on average, even in half an hour, the solutions found by solving the cloneless model in two hours of computations.

2.1 Selection And Criteria Inclusion Of The Analysed Studies

An evaluation criteria is presented in Table 1. A systematic review principle proposed by [14], was used. The second stage which is conducting the review started by searching literature using online databases such as Elsevier Scopus, Google scholar, Springer Link, Science Direct, and Emerald Insight. Keyword search was undertaken using online databases pertaining to the following themes to collect relevant material that aligned with the goal and direction of this research:

1) Modelling the dynamics of infrastructure projects
2) System dynamics modelling in construction/infrastructure projects within the electricity industry

Besides searching on the online databases, relevant journal articles about construction project and on-time delivery of infrastructure projects that were published, were also collected. These journals included the International Journal of Project Management, the Journal of Construction Engineering and Management, the Journal of Management in Engineering, the Journal of Civil Engineering and Management, and the Journal of Construction Management and Economics. This review only includes studies published within the last twenty years (2001-2021). The criteria as tabulated in Table 1, it comprises a general evaluation of the research subject, as well as limiting reviewed papers to those written in English, ensuring that the reviewed articles are relevant to the research area.

2.2 Adaptive Simulated Annealing

Referring to the problem independence and general model characteristics, simulated annealing has been applied to various kinds of optimization problems and successfully obtained great results[15]. Simulated Annealing belong to metaheuristic metaheuristics which is a procedure to solve complex optimization problem in good enough solution[16].

Optimization problems are mostly solved using iterative methods. An iteratively performed improvement begins with generating the initial state, or setting values for variables. Simulated annealing can be analogous to minimizing the function of costs and the process of material changes while minimizing that energy. When the material wants to be crystallized from the liquid phase, it needs to be cooled slowly. At each temperature during the annealing process, the material is in equilibrium: The probability of being in a particular state is determined by the Boltzmann distribution for that temperature. As long as the temperature continues to decrease, the distribution becomes concentrated in the lower energy state. When in the end the temperature reaches zero, only the lowest energy state has non-zero probability. In However, if it cools too quickly, the material does not have time to reach equilibrium. Because if so, there will be various defects that cause the material structure to become frozen.

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The development carried out in this study is to apply rejection less methods or without rejected moves methods based on the research done by Greene and Supowit (1986) named as Adaptive Simulated Annealing (ASA)[17]. Their work simplifies the logic to accept the new solution. It only accepts the better solution. For instance, if the result from the new solution modification is not as good as the previous solution, the new solution will be rejected, and the next iteration will be run to find another new solution. The Adaptive SA algorithm simplifies the logic to accept the new solution. It only accepts the better solution[17]. For instance, if the result from the new solution modification is not as good as the previous solution, the new solution will be rejected, and the next iteration will be run to find another new solution.

3. Method

This paper aims to find out the best results of the Electric Vehicle Routing Problem for each instance. This research was carried out on the basis of Mavrovouniotis's dataset [18]. EVRP has been studied by several researchers and was solved using several solution approaches. However, the optimal value has not yet been obtained, so there is an opportunity to develop a better solution approach. This paper proposes an Adaptive Simulated Annealing algorithm (ASA) that is capable of adjusting the operator to change the solution dynamically. To determine the performance of this algorithm, a comparison is needed. Some of the algorithms that have been proposed for EVRP are Variable Neighborhood Search (VNS), Simulated Annealing (SA), and Genetic Algorithm (GA) as shown in Table 1.

Table 1. Algorithm comparison

No	Algorithm	Total Distance
1	Variable Neighborhood Search	384.67
2	Simulated Annealing	384.67
3	Genetic Algorithm	384.67

3.1 Mathematical Formulation

In this paper, the fundamental problem we are committed to solving is to construct routes for a set of vehicles, which take all users from their origins to destinations by meeting the user's time requirement, while not violating the vehicle's load (capacity) and battery power constraints. The mathematical model used in this study refers to [18] that aims to minimize the total distance of constructed route that have limitation on vehicle capacity and battery capacity. Each vehicle depart from depot and return back to depot after visited some customers. In their work, it assumed battery level is 100% after recharging to charging station. The complete EVRP model is as follows.

Objective Function:

$$\min z = \sum_{i \epsilon V, j \epsilon V, i \neq j} d_{ij} x_{ij} \tag{1}$$

Subject to:

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

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

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

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

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

$$y_j \leq y_i - h d_{ij} x_{ij} + Q(1 - x_{ij}), \forall i \in I, \forall j \in V, i \neq j \tag{7}$$

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

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

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

The objective function (1) is the equation to minimize the total travel distance. Equation (2) guarantee all customer to be visited. Equation (3) handles charging station connections. Equation (4) to ensure that each customer only visited by one vehicle and only one vehicle left its customer node. formula. Equation (5) and (6) ensuring that all customer demands are met by guaranteeing a non-negative payload upon arrival at each node, including depots. Equation (7), (8), and (9) ensure that battery level is not below zero and not more than its battery capacity. Equation (10) define a set of binary decision variables to visits the customer node or not, 1 to define that customer node is visited, while 0 if that customer is not visited. Variables ui indicates remaining capacity and yi indicated remaining battery level on its arrival customer node $i \in V$.

3.2 EVRP Dataset

The dataset that used to compare the performance of each algorithm is dataset which is an instance of the dataset for EVRP which has detailed specifications in Table 2[18]. Detailed specification include the number of depot, customers, vehicles, and number of charging stations, as well as the vehicle capacity, battery capacity, and battery energy consumption. The entire node of both depot and customer has x and y coordinates, and also the demand which can be seen in Table 3.

3.3 General Steps of ASA on EVRP

The steps for optimizing electric vehicle routing problems using adaptive simulated annealing are depicted in the flowchart in Fig. 1. We begin with inputting data into a programming language. In this study, the programming language used was Python. The data input process was assisted by the pandas module and converted into a matrix using the numpy module so that the distance calculation process could be carried out simultaneously. Several parameters in adaptive simulated annealing such as initial and final temperature, alpha, and decay need to be stated for this EVRP optimization.

Table 2. Specification Data

No	Dataset Specification	Amount
1	Number of depot	1
2	Number of customers	21
3	Number of vehicles	4
4	Number of charging stations	8
5	Vehicle capacity	6000
6	Battery capacity	94
7	Battery energy consumption	1.2

Pseudocode Adaptive Simulated Annealing for Electric Vehicle Routing Problem

1. Set parameter (T0, TF, alpha, decay)
2. Generate initial solution TSP
3. Handling capacity constraint
4. Handling battery level constraint
5. Calculate objective value
6. Set initial operator weight
7. **While** (t < Tfinal) **do**
8. Select operator based on its weight
9. Solution modification Xnew ← X
10. Handling capacity and battery level constraint
11. Calculate fitness value
12. **If** f(Xnew) < f(X) **do**
13. f(X) = f(Xnew)
14. X = Xnew
15. **End If**
16. Update weight best on previous performance
17. **End While**
18. Return X and f(X)

3.4 EVRP Initial Solution

All data and parameter that has been mentioned become the basis for the EVRP solution search process which starts from generating an initial TSP (Traveling Salesman Problem).

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Table 3. Entire Node of Depot

Label	X	Y	Demand
Depot	145	215	-
Customer 1	151	264	1100
Customer 2	159	261	700
Customer 3	130	254	800
Customer 4	128	252	1400
Customer 5	163	247	2100
Customer 6	146	246	400
Customer 7	161	242	800
Customer 8	142	239	100
Customer 9	163	236	500
Customer 10	148	232	600
Customer 11	128	231	1200
Customer 12	156	217	1300
Customer 13	129	214	1300
Customer 14	146	208	300
Customer 15	164	208	900
Customer 16	141	206	2100
Customer 17	147	193	1000
Customer 18	164	193	900
Customer 19	129	189	2500
Customer 20	155	185	1800
Customer 21	139	182	700
Charging Station 1	137	193	-
Charging Station 2	137	213	-
Charging Station 3	137	234	-
Charging Station 4	137	254	-
Charging Station 5	155	193	-
Charging Station 6	155	213	-
Charging Station 7	155	234	-
Charging Station 8	155	254	-

TSP initiation is used to determine the order of visits to customers without regard to the demand, capacity & battery of the vehicle. The initial solution to TSP is a random number of customers to be visited. In this study, there were 21 customers who had to be visited, so that random TSP initiation would look like in Fig. 2.

The previous TSP solution was one whole route which in EVRP did not allow sending all requests using one vehicle because it had limited battery & load capacity. Therefore, a handling constraint is needed so that the route is divided into several available vehicles. The route deployment is done by selecting vehicles randomly as illustrated in Fig. 3. The constructed solution of CVRP which is then developed into Electric Vehicle Routing based on battery capacity constraints.

The CVRP solution that has been found is then converted into EVRP based on battery capacity and energy consumption. Each vehicle departs from the depot with a full battery. Battery capacity continues to decrease every time it visits a consumer until it reaches a critical level to decide on charging or continue delivery until it breaks down. When the time to charge comes, the vehicle will look for the nearest charging station. The nearest charging station is obtained by calculating the distance between the alternative charging station and the line segment between the coordinates of the last consumer before charging and the first consumer after charging.

3.5 Solution Modification using ASA

The initial EVRP solution containing the sequence of nodes and charging stations was still not good enough to be executed due to very random and inefficient visit sequences, so it was necessary to modify the solution to obtain the shortest route. The modification of EVRP solutions in this study uses a metaheuristic approach in order to obtain solutions in a reasonable time. The metaheuristic used is Adaptive Simulated Annealing (ASA) which is inspired by the process of slowly cooling the metal.

ASA in this study modified the solution with 3 operators, namely swap, insert, and reverse. Swap modifies the solution by swapping 2 randomly selected nodes. The swap operator modifies the solution by inserting the first node of the 2 randomly selected nodes just before the second node. The reverse operator modifies the solution by flipping the order of the nodes in the range between 2 randomly selected nodes. An example of a solution modification of each operator is shown in Fig. 5. Operator selection is done adaptively based on the historical performance of that operator. Operators that more often produce better solutions, will have greater weight to be selected as operators in later iterations.

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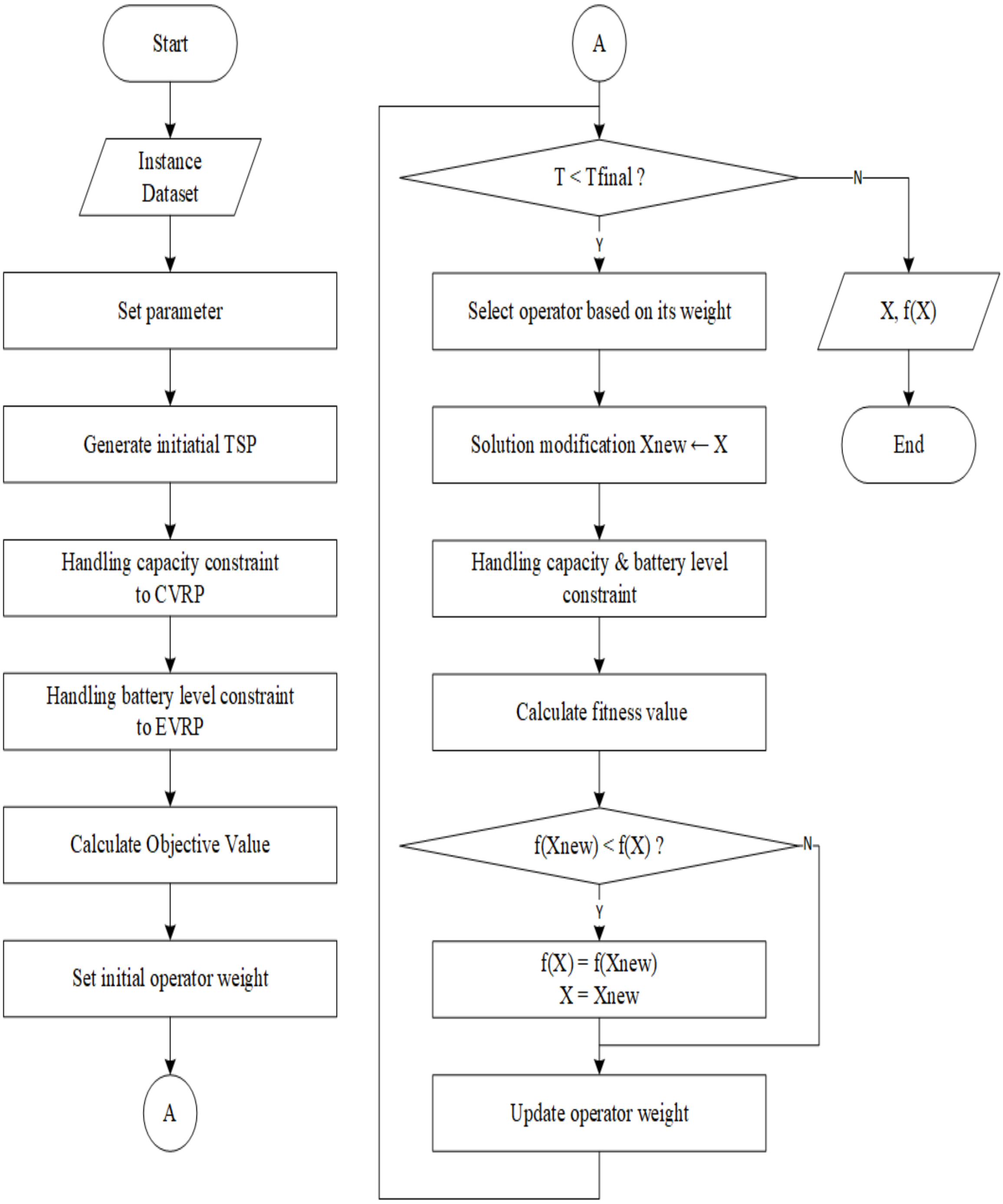

Fig. 1 Flowchart of ASA for EVRP

19	16	17	6	13	4	2	7	12	20	14	1	10	21	9	5	18	15	11	3	8

Fig. 2 TSP Initial solution

Random Node	4	1	3	5	2
Random Vehicle	2	1	1	2	1

Route of Vehicle 1 : depot → 1 → 3 → 2 → depot
Route of Vehicle 2 : depot → 4 → 5 → depot

Fig. 3 Conversion of TSP to CVRP

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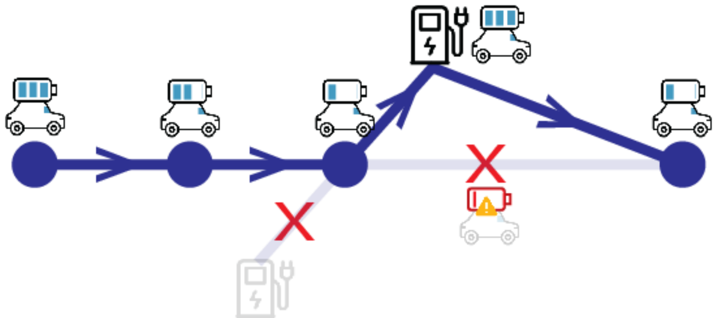

Fig. 4 Decision to charging station

Swap	4	1	3	5	2	→	4	2	3	5	1
Insert	4	1	3	5	2	→	4	3	5	1	2
Reverse	4	1	3	5	2	→	4	2	5	3	1

Fig. 5 Operator

4. Results

In this study, EVRP cases were taken from the E-n22-k4 dataset [18] which had 22 nodes, 4 vehicles, and 8 charging stations. Of the 22 nodes, there is 1 depot as the departure and arrival point for each vehicle, and the other 21 nodes are randomly scattered customer locations that can be seen in Fig. 6. The red dot is the depot, the green dot is the charging station, and the blue dot is the location of each customer In addition, there are also other data that are fundamental to EVRP, namely vehicle capacity, battery capacity, and vehicle battery power consumption which have values of 6000, 94, and 1.2, respectively.

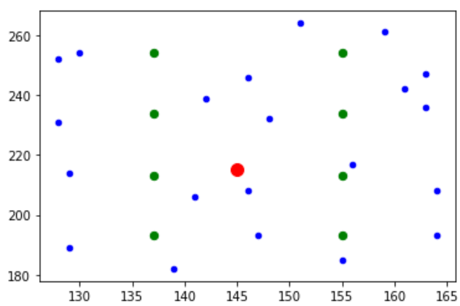

Fig. 6 Coordinates of E-n22-k4 dataset

According to [17], the elimination of rejection of candidate moves can increase the efficiency of the Simulated Annealing algorithm and have an impact on the significant speed-up of offering simpler moves. Its implementation in EVRP has also experienced something similar. While rejection moves or what is popularly referred to as the metropolis criterion is still attached to the Simulated Annealing algorithm, it is difficult for the algorithm to exploit deeper solutions. The metropolis criterion provides high flexibility to accept any solution in the early to mid stages, so it is very difficult to tolerate a new solution in the middle to the end of iterations. For these shortcomings, this study refers to the idea of [17] which abolishes rejection moves and increases the exploitation power of solutions by using adaptive mechanisms in simulated annealing.

The proposed Adaptive Simulated Annealing (ASA) for Electric Vehicle Routing Problem (EVRP) was coded in Python programming language and run on a computer with specification Intel Core i5-4200U and 4GB RAM. This algorithm uses several parameters such as initial temperature (To), final temperature (Tf), Alpha, and decay for its adaptive mechanism.

Table 4. Initial Parameters

Parameter	Value
To	100
Tf	0.01
Alpha	0.001
Decay	0.9

EVRP has been run using ASA without rejected moves and obtained satisfactory results because it can outperform other algorithms such as VNS, SA, and GA. The total distance formed from this ASA algorithm is 383.77, which means it is better than the best-known solution which has a total distance of 384.67. The order of the

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nodes traversed on this route can be seen in Table 5 and also in Fig. 8. The convergence rate in the ASA algorithm also looks quite good due to the balanced exploration and exploitation process. At the initial stage of the iteration, the exploration process looks quite aggressive which can be seen on the left side of Fig. 7. The exploration process in this algorithm occurred a significant decrease in objective value due to the discovery of better solutions. Starting around the 4000th iteration which is the middle of this algorithmic process, the decrease in objective value is not very significant because it goes into the exploitation process which is the stage to change a small part of the previous solution.

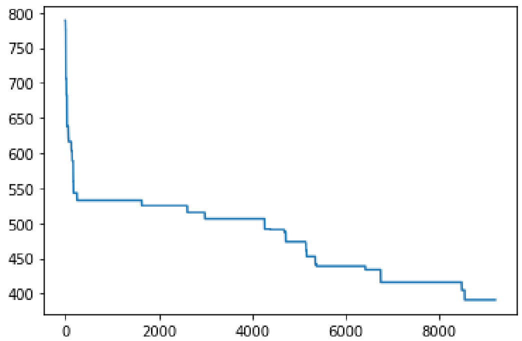

Fig. 7 Convergence rate

Table 5. Initial Parameters

Vehicle	Constructed Route	Distance
1	11 - 4 - 3 - 1 - 2 - 29 - 6 - 8	131.33
2	14 - 17 - 21 - 20 - 18 - 15	99.27
3	10 - 7 - 5 - 9 - 12	81.48
4	16 - 19 - 13	71.69
Total Distance		383.77

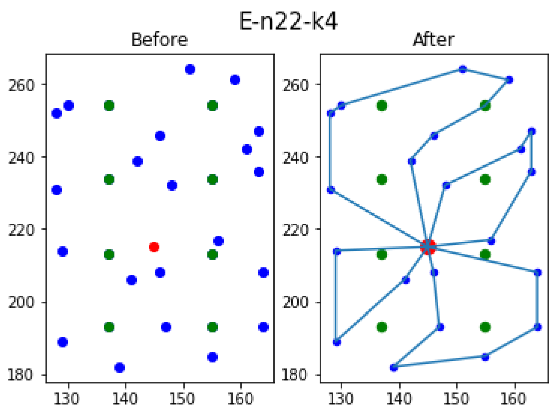

Fig. 8 Final route

5. Conclusions

The Electric Vehicle Routing Problem has been solved using the Adaptive Simulated Annealing approach. The initial solution is generated from a sequence of random nodes in the form of a TSP converted to CVRP based on carrying capacity, then converted into an EVRP solution by looking for the nearest charging station and adjusting the remaining battery power. The solution that has been formed is then modified using one of the three operators adaptively. The three operators used are swap, insert, and reverse. The ASA algorithm on EVRP was tested for performance on an instance of the EVRP dataset and obtained better results from the best-known solutions.

It is crucial to strategically plan the distribution network, as disruptions to the network or capital investment can affect the objective function of minimizing travel distance. Therefore, this study can be further improved by incorporating resilience metrics into the modeling. These resilience metrics will improve the plan's resilience to road disruptions. Examples of these metrics include buffer inventories, and also route plans that allow merging capacity in cases of vehicle breakdowns or road accidents. Buffer inventories greatly improve a logistics network's resilience at a low cost [19]. During disruptive events, sharing idle inventory across supply chain network nodes can significantly minimize supply shortages [20].

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