Optimization of heterogeneous VRP model by considering recharging station using mixed integer programming

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Article Info

Article history:

Received May 12, 2023
Revised May 29, 2023
Accepted Jun 4, 2023

Keywords:

Heterogeneous vehicle routing problem
Mixed integer programming
Model
Optimization

ABSTRACT

Transportation activities require substantial costs: drivers, fuel, vehicle maintenance, vehicle and equipment procurement capital, and administrative activities. In the vehicle routing problem (VRP), all vehicles have the same load capacity. But in reality, the company has vehicles with different abilities. The heterogeneous vehicle routing problem (HVRP) is a variant of VRP. Transportation is a source of pollution. Therefore, electric vehicles are starting to replace fossil fuel vehicles. However, a few electric vehicle recharging stations remain, especially in Indonesia. Consequently, the authors build a heterogeneous vehicle routing problem model by considering the filling station using mixed integer programming. This research aims to create a model by determining distribution routes with minimum costs from several capacities of electric-powered freight fleets with different capabilities by considering refilling stations. Research contributions realize the transition towards sustainable energy, one of the priority issues in Indonesia's G20 presidency.

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1. INTRODUCTION

In an industrial company's distribution chain operation, transportation is crucial [1]. Transport is becoming more dynamic along with customer demand or company growth [2]. The vehicle routing problem (VRP), which aims to reduce the overall cost of transportation to visit a group of clients via multiple routes starting and finishing at the depot, is typically used to model the distribution task of a logistics organization [3]. One of the uses of VRP is to reduce environmental pollution [4]. VRP is a well-known and well-studied field. This research was first introduced by Dantzig and Ramser in 1959 [5]. VRP is a development of the traveling salesman problem (TSP) method where delivery is carried out by only 1 vehicle [6]. The most common problem encountered in logistics activities related to transportation is the determination of vehicle routes.

VRP is a problem in finding ways by considering the minimum cost and minimum time starting from the depot to distribution points that can only be served by one vehicle with many different requests that are scattered and end up returning to the depot. Still, the number of requests in one route can be, at most, the vehicle's capacity. In VRP, each vehicle has the same capacity. In reality, the cars owned by the company do not have the same power, so VRP is inappropriate for solving heterogeneous vehicle problems. In addition, due to the geographical location of customers, companies need to have various types of vehicles with multiple capacities to serve commodities to customers [7].

Therefore, a variant of the VRP was born to solve the VRP problem for heterogeneous vehicle capacities. The heterogeneous vehicle routing problem (HVRP), a variation of VRP, was first presented in 1984 by Golden, Assad, Levy, and Gheysens. HVRP is a VRP problem that adds different types of vehicles in capacity. HVRP aims to determine an effective fleet structure and routing strategy to reduce overall costs [8]. HVRP is more realistic since it takes into account situations where different types of vehicles or heterogeneous fleets may be used. Long-distance logistics transportation in cities has been significantly challenged by the e-commerce and express delivery sectors' explosive growth, which has also resulted in serious environmental issues like greenhouse gas emissions and pollutant emissions [9]. The transportation sector generates the largest share of greenhouse gas emissions [10]. Greenhouse gas emissions from transportation primarily come from burning fossil fuel for our cars, trucks, ships, trains, and planes [10]. The increasing number of private vehicles must be watched out for regarding environmental problems because 34 million liters per day are produced by private cars [10]. Data from the European commission [11] shows that the transport system is one of the main drivers of greenhouse gas emissions, accounting for 25% of CO2 emissions. The ratio is expected to double by 2050.

Among alternative fuel vehicles, electric vehicle options remain the most attractive [12]. Electric vehicles (EV) are a way to reduce emissions from mobility [13]. A NASA study in Ou *et al.* [14] shows that using electric vehicles requires the following benefits: electric vehicles emit fewer carbon emissions, significantly improve air quality, and electric vehicles need lower operating and maintenance costs. Electric vehicles can offer faster acceleration fast, are It is smoother and quieter, and it can be utilized extensively in noisy urban locations. The Indonesian Ministry of Environment and Forestry requires all new gasoline vehicles meet Euro 4 emission standards starting in September 2018 and all new diesel vehicles to meet Euro 4/IV emission standards starting in April 2021, replacing the current Euro 2/II emission standard requirements [15].

However, there are some disadvantages to electric vehicles. Users require greater autonomy, more frequent and lengthier recharges, and a lack of charging infrastructure despite the expensive purchase price [16]. The number of charges at stations is constrained in practice, thus they might not be accessible when a car arrives. Because of this, it could need to wait in line before being recharged, and routing decisions must take this waiting time into account [17]. An automobile with an internal combustion engine can be charged on average in 3 minutes, while an electric vehicle can be charged in 15 to 6 hours. Charging speed varies depending on vehicle type and battery technology [18]. This, of course, results in increased travel time for a travel route. There is also a range of anxiety syndromes, namely the user's fear that the battery will run out before completing a trip or arriving at a charging station [19].

The Indonesian government must support the smooth running of the electrification vehicle ecosystem, such as infrastructure, namely charging stations. Thus, between manufacturers who are improving the transition of production of diesel-fueled freight transport fleets to electric-powered freight transport fleets and the government preparing the infrastructure for electric vehicle ecosystems, this will result in an accelerated conversion from diesel to electric fleets. To replace conventional vehicles, electric vehicles must provide the same level of comfort on long-distance trips through adequate charging infrastructure. In Indonesia itself, charging stations still need to be improved. To increase the vehicle's electricity usage, charging stations should be installed, and the following costs should be considered. These replenishment visits should be regarded as in route planning to prevent lengthy detours and inefficient vehicle routing, especially if there are few nearby filling stations. The strength of the selected charging station and the amount of energy charged at each station determine the optimal route and speed to travel. Also, the route chosen affects the number of charging stations and the quantity of energy to charge, thus these variables interact with one another [20].

As of Nov. 17, 2022, Indonesia had 439 charging stations in 328 locations and 961 battery swap stations in 961 locations spread across the country, most of them are located in Java, Energy and Mineral Resources Ministry data show [21]. The number of public electric vehicle charging stations (SPKLU) available in Indonesia is increasing. Based on PLN data, as of the end of 2022, it has installed 570 SPKLUs across Indonesia [22]. The charging stations offer three types of charging services, namely, medium charging, fast charging, and ultra-fast charging [22]. PLN is intensively constructing SPKLUs to ensure the availability of EV charging infrastructure so that the Indonesian people do not hesitate to shift to EVs, which are more environmentally friendly [22].

This research builds on the classic VRP involving electric vehicles and recharging operations. In the literature review, electric vehicle routing problem (EVRP) has been expanded by considering several features, such as types of charging stations, minimization of total energy consumed, depots, the uncertainty of energy consumption, heterogeneous electric vehicles, time window, and charging with nonlinear functions. The objective of this problem is to minimize the total travel distance. Based on the problems above, the authors develop a model of heterogeneous vehicle routing problems by considering that there are few and limited charging stations. Research contributions realize the transition towards sustainable energy, one of the priority issues in Indonesia's G20 Presidency.

2. METHOD

2.1. Research framework

Explaining the research framework is a conceptual structure that presents the framework, theory, and methods used in this research. The research framework assists researchers in planning, carrying out, and analyzing research in a structured and systematic way. Figure 1 the following is the framework of the research.

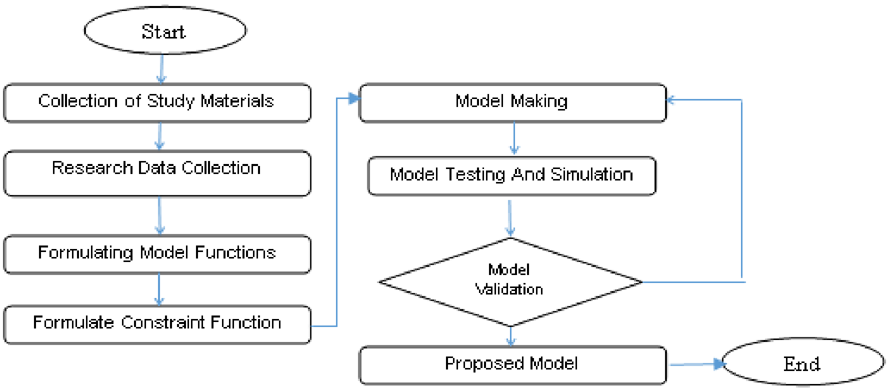

Figure 1. Research work framework

The following is an explanation of the research stages according to Figure 1:

a. Collection of study materials: this stage involves gathering information, references, literature, and other resources relevant to the research topic. This study material is used to understand the issues studied and develop a theoretical framework.
b. Research data collection: at this stage, the researcher collects the data needed to answer research questions or test the hypotheses that have been formulated. Data collection methods such as observation, interviews, questionnaires, or document analysis can vary.
c. Formulate the model function: after the data is collected, the next step is formulating the model function. This means developing approaches or concepts that will be used to analyze or explain the data that has been collected. Model functions can be mathematical formulas, theories, or conceptual frameworks that describe the relationships between variables or constructs in research.
d. Formulate constraints: this stage involves identifying and formulating obstacles that may arise in the research process. These constraints can be in the form of limited data, resources, time, or methodological problems. Defining conditions helps in devising an effective research strategy and foreseeing potential obstacles that may be encountered.
e. Model building: after formulating the function of the model and identifying the constraints, the next step is building the model. This involves developing a structure or framework that systematically applies model functions to research data. Modelling also consists in selecting a technique or method of analysis appropriate to the research objective.
f. Model testing and simulation: the model is tested and simulated using the relevant data at this stage. Testing and simulation aim to validate whether the model can produce accurate results by research objectives. The model can be revised or adjusted if the results do not match.
g. Model validation: the model validation stage involves more comprehensive and in-depth testing to ensure that the model created can produce consistent and reliable results. Validation involves statistical analysis, comparison with previous research, and assessing the model’s suitability with existing data.
h. Proposed models: the final stage is to develop the proposed model based on research results and model validation. The proposed model is the final result of the research and reflects the research contribution to the field under study. This model can include policy recommendations, new frameworks, or solutions based on findings.

2.2. Related research

Zhang *et al*. [23] investigates the problem of capacitated green vehicle route, a particular instance of the EVRP that does not take recharging time into account. The author suggests two techniques to solving the problem, including two levels of heuristics and metaheuristics constructed using the ant colony system. In the first two heuristic steps, the delivery path is found using a greedy neighborhood approach to solve the traveling salesman problem (TSP). In order to develop a workable solution, filling stations and depots are inserted in the TSP line in accordance with the leftover fuel and product residue. The implementation of the ant colony system performed 38.27% better than the two heuristic stages, according to the results.

G-Echeverri *et al*. [24] analyzes EVRP offers services to two different customer groups. Customers who require a specific product transported are included in the first group, while customers who want to send a specific product to the depot are included in the second group. Also, in order to solve this issue, the first group of customers must be visited before the second.

Felipe *et al*. [25] EVRP was presented with a variety of technologies and partial recharging. In contrast to the conventional EVRP, this article takes into account different kinds of charging stations and provides electricity at the stations. The pace and price per filling unit are regulated for each type of station. The overall replenishment cost, which includes both fixed and variable costs, is what this article tries to reduce. The battery charge divided by the anticipated maximum number of recharges yields the fixed cost of each recharge procedure. The variable cost of replenishing measures varies according to the type of charging station and is proportionate to the amount of electricity being recharged. Three different heuristics are used by the authors of this work to solve difficulties. The first kind is a constructive heuristic, which works fast to find a workable solution. The second type is the variable neighborhood search (VNS) heuristic, which makes use of the relocation reloads, 2 opt, and reinsertion neighborhood search operators. The simulated annealing (SA) algorithm is the last type.

Lin *et al*. [26] authored a paper on basic EVRP that attempts to reduce the overall cost, which includes travel time, battery charging waiting time, and battery charging prices. Also, the delivery and collection of products are affected by this issue. The vehicle load and travel speed are also taken into account when calculating costs. While vehicle load fluctuates along the route, each arc's travel speed is taken to be constant. With the use of case studies, the authors further emphasize the need for the routing plan to take load impacts into account.

Shao *et al*. [27] explains research on EVRP that aims to reduce the total of fuel expenses, trip costs, and vehicle fixed costs. This analysis makes the assumptions that a full charge policy is in place and that the charging time is consistent. The authors use a hybrid genetic algorithm that combines local search with GA to get around this issue. Zhang *et al.* [28] EVRP, which aims to reduce the overall energy consumed by electric vehicles, was started. Many variables, including the distance traveled, the weight of the vehicle, the speed, and the engine efficiency, affect how much power is used. This problem also establishes a complete charge policy without taking charging time into account. As a result, each charging station has zero service time. The study suggests an algorithm for ant colonies and an adaptive extensive neighborhood search (ALNS) heuristic [29] as they get closer to a solution. The researches also carried out trials based on a collection of self-generated situations and discovered that the ant colony method performed better than the ALNS heuristic in terms of explanation and computation time for large problems and might produce a near-optimal solution for lesser cases, [30] outlined the four goals of the multi-depot EVRP: maximization of revenue, minimization of expenditures, reduction of journey time, and reduction of CO_2 emissions. The enhanced ant colony optimization algorithm is used to overcome this issue.

The actual amount of energy used is uncertain because of the weather, the state of the roads, the actions of the drivers, and a number of other difficult-to-predict factors. To resolve this issue, Pelletier *et al.* [31] provides EVRP with a comprehensive optimization framework to deal with the uncertainty of energy usage. Because each arc is assumed to have an expected rate of energy usage when the vehicle is empty (kWh) and an expected rate of energy use when the vehicle is complete (kWh/kg), this problem differs from the deterministic EVRP. The actual amount of energy utilized differs from what is anticipated because of the unpredictable environment. To reduce the overall fixed cost of electric vehicles, the worst-case energy cost, the overall maintenance cost based on the total number of miles driven, the authors transformed the uncertainty problem into a deterministic mixed integer programming (MIP) model. To create the best possible solutions for small instances of the problem, we start by using a cutting plane algorithm. To discover the best answer for important scenarios, a two-phase heuristic method based on extended neighborhood search (LNS) was created.

Boudallaa *et al*. [32] proposes the speed control of an asynchronous motor (AM) using the H∞ Antiwindup design. The collected practical speed is used as a speed reference for conventional vector control. The H∞/Antiwindup controller of the direct rotor flow-oriented control is used to improve the performance of conventional vector control and optimize the energy consumption of the drive train. The effectiveness of the proposed control scheme is verified by numerical simulation. The results of the numerical validation of the proposed scheme showed good performance compared to conventional vector control. The speed control systems are analyzed for different operating conditions. The simulation results of the improved vector control of the AM are used to validate this optimization approach in the dynamic regime, followed by a comparative analysis to evaluate the performance and effectiveness of the proposed approach.

A practical model based on a TMS320F28379D embedded board and its reduced voltage inverter (24 V) is used to implement the proposed method and verify the simulation results.

Gorbunova and Anisimov [33] aims to examine the operation of the existing charging infrastructure. This will provide an opportunity to develop approaches to the energy supply of charging infrastructure and city grids from renewable energy sources. The article analyses the number of charging sessions yearly, monthly and daily. This data allowed us to construct a charging session number curve and suggest ways to carry out the next stage of this research.

Kapeller *et al*. [34] aims to improve and cover the requirements for electric vehicles (EV) by using heating, ventilation, and AC (HVAC) modeling. The researchers wanted to hide the impact the HVAC system had on EV performance and energy consumption. This study uses a modeling approach to simulate the behavior of the HVAC system in an EV. This involves developing a mathematical model that takes into account various factors such as vehicle size, thermal properties, environmental conditions, and HVAC settings. The model is then used to evaluate the different HVAC configuration configurations and their effect on the energy consumption of all EVs. The research findings, presented in the form of analysis and results, provide insight into the impact of HVAC systems on energy efficiency and EV coverage. This study applies the importance of modifying the HVAC configuration to achieve a balance between occupant comfort and energy consumption in electric vehicles.

3. RESULTS AND DISCUSSION

The electric vehicle routing problem (EVRP), which involves electric vehicles and charging procedures, is a development of the traditional VRP. The EVRP has been expanded in the literature review by taking into account a number of features, including different charging station types, minimizing the overall energy consumed, depots, the uncertainty of energy consumption, heterogeneous electric vehicles, time window, and charging with nonlinear functions. Previous research found two primary studies regarding EVRP with a time window [3] and filling with a nonlinear function [35].

The model proposed by the author is that vehicle fleets have different (heterogeneous) capacities, each customer will only be visited once, the depot only consists of one, and each transport fleet will start from the depot and end at the depot. This model uses a MIP approach. This model minimizes the total travel distance. And ensure that each customer must be served precisely once. The authors transform the uncertainty problem into a deterministic MIP model to reduce the total fixed cost of electric vehicles; the total maintenance cost proportional to the total distance travelled, and the worst-case energy cost. First, we use a cutting plane algorithm to generate optimal solutions for small instances of the problem. Then, a two-phase heuristic method based on extensive neighbourhood search (LNS) was developed to find the optimal solution for significant cases.

So far, research investigating standard EVRP has been minimal. Most of the literature review has focused on extensions and variants of the standard EVRP. Pelletier *et al.* [31] presented EVRP with multiple technologies and partial recharge. Unlike the standard EVRP, this paper considers various types of charging stations and provides electricity at the charging stations. Each type of station has a predetermined speed and cost per filling unit. This paper aims to minimize the total replenishment cost, which consists of fixed and variable costs. The fixed price of each recharge action is determined by the charge of the battery divided by the estimated maximum number of recharges. The variable cost of renewing measures is proportional to the amount of electricity being recharged and also depends on the type of charging station. Researchers in this paper apply three types of heuristics to solve problems. The first type is the constructive heuristic which aims to produce a feasible solution quickly. The second type is the variable neighbourhood search (VNS) heuristic, which uses three neighbourhood search operators: relocation reloads, two opt, and reinsertion. The last type is the SA algorithm. In reality, energy use is unknown due to weather and road conditions, driver behaviour, and several other parameters that are difficult to determine precisely. To overcome this problem, Pelletier *et al.* [31] proposes an EVRP with uncertainty in energy consumption and a robust optimization framework to overcome this uncertainty. This problem is different from the deterministic EVRP; this problem assumes that each arc (i, j) has an expected energy usage rate when the vehicle is empty, $a_{i,j}$ (kWh), and an expected energy usage rate when the vehicle is complete, $b_{i,j}$ (kWh/kg). Due to the uncertain environment, the actual amount of energy used differs from what is expected. The authors turned the uncertainty problem into a deterministic MIP model to minimize the total fixed cost of electric vehicles, the total maintenance cost proportional to the total distance travelled, and the worst-case energy cost. First, we use a cutting plane algorithm to generate optimal solutions for small instances of the problem. Then, a two-phase heuristic method based on extensive neighbourhood search (LNS) was developed to find the optimal solution for significant cases.

The novelty of this research is a model that determines distribution routes with minimum costs from several capacities of electric-powered freight transport fleets with different capabilities by considering recharging stations. The mixed integer programming (MIP) model of the EVRP standard is presented. Suppose

V' the collection of vertices with $V' = V \cup F'$, where $V = \{1, \dots, n\}$ denoted n as the set of customers and F' as the set of dummy vertices associated with set F of the filling station. Vertex 0 and $N + 1$ represents the exit and entry of the depot, and each route must start at vertex 0 and end at vertex $N + 1$. In addition, it is defined as well $F_0' = F' \cup \{0\}, V_0' = V' \cup \{0\}$, and $V_{0,n+1}' = V' \cup \{0, n + 1\}$. EVRP is defined on a complete and directed graph $G = V_{0,n+1}', E$ with a set of arcs $E = \{(i,j)|i,j \in V_{0,n+1}', i \neq j$. Each arc has a distance $d_{i,j}$, traveling time $t_{i,j}$, and constant battery consumption rate h (per unit distance), in other words, crossing this arc consumes $hd_{i,j}$ battery power. C fleet of identical electric vehicles with charge capacity a and battery capacity Q are placed at the depot. When leaving the depot, the electric vehicle has a full battery charge. Each vertex $i \in V_{0,n+1}'$ has a positive value request q_i, which is 0 if $i \notin V$, and service time $s_i(s_0 = s_{n+1} = 0)$. At each charging station, the difference between the current battery level and Q is the charging rate g (assumed to be on a full charge policy). Each customer must be visited by exactly one vehicle (separate shipments are not allowed). Decision variable τ_i is the arrival time, decision variable u_i is the remaining cargo, and decision variable y_i is the remaining battery power upon arrival at vertex $i \in V_{0,n+1}'$ assume $x_{i,j}(i \in V_0', j \in V_{n+1}', i \neq j$ is a binary decision variable equal to 1 if arc (i,j) traversed, or 0 if not. The goal of this challenge is to reduce the overall journey distance. The following is a description of the EVRP MIP model:

$$min \sum_{i \in V_0', j \in V_{n+1}', i \neq j} d_{i,j} x_{i,j} \tag{1}$$

With constraints:

$$\sum_{j \in V_{n+1}', i \neq j} x_{i,j} = 1, \forall i \in V \tag{2}$$

$$\sum_{j \in V_{n+1}', i \neq j} x_{i,j} \leq 1, \forall i \in F' \tag{3}$$

$$\sum_{j \in V_{n+1}', i \neq j} x_{j,i} - \sum_{i \in V_0', i \neq j} x_{i,j} = 0, \forall j \in V' \tag{4}$$

$$\tau_i + (t_{i,j} + s_i)x_{i,j} - M(1 - x_{i,j}) \leq \tau_j, \forall i \in V_0, j \in V_{n+1}', i \neq j \tag{5}$$

$$\tau_i + t_{i,j}x_{i,j} + g(Q - y_i) - (M + gQ)(1 - x_{i,j}) \leq \tau_j, \forall i \in F', j \in V_{n+1}', i \neq j \tag{6}$$

$$0 \leq u_j \leq u_i - q_i x_{i,j} + C(1 - x_{i,j}), \forall i \in V_0, j \in V_{n+1}', i \neq j \tag{7}$$

$$0 \leq u_0 \leq C \tag{8}$$

$$0 \leq y_j \leq y_i - hd_{i,j}x_{i,j} + Q(1 - x_{i,j}), \forall j \in V_{n+1}', i \in V, i \neq j \tag{9}$$

$$0 \leq y_j \leq Q - hd_{i,j}x_{i,j}, \forall i \in F_0', j \in V_{n+1}', i \neq j \tag{10}$$

$$x_{i,j} \in \{0,1\}, i \in V_0', j \in V_{n+1}', i \neq j \tag{11}$$

where: d is distance between customers;x is visit; V is Vertex set; F is recharging station; t is travel time 37; s is service time; M is number of vehicles; g is filling rate; Q is battery capacity; y is remaining battery power; gQ is full charge; C is load capacity; hd is battery power consumption;

This is a comparatively large positive value in the model mentioned above. The overall travel distance is minimized using objective function (1). The second constraint ensures that each client must be served exactly once (2). Each dummy filling station must only be used once, according to constraint (3). In order to maintain the travel flow, constraint (4) represents a flow conservation restriction. The relationship between and, which are connected by two vertices and are visited in order, is defined by constraints (5) and (6). Limitations (7) and (8) meet each customer's need. Last but not least, restrictions (9) and (10) specify that the battery charge level cannot go to zero. Furthermore, the above model is tested for optimization.

3.1. Description of the method of completion

Provide an example of a constraint-based optimization issue and its viable or solution region. The set $x: g(x) = b$, a constant, is referred to as the feasible region or the solution if $g(x)$ is a constraint function of the optimization problem with $g = Rn \rightarrow R$ region of the optimization problem. The definition of the function $g(x)$ for combinatorial optimization is the mapping $g: \{0,1\}, n \; \{0,1\}$. To obtain a feasible area, most methods for solving combinatorial optimization problems propose a feasible region, that is, an area bounded by problem constraints after relaxing the count or binary terms of the variables. For example, the branch and bound and field slice methods. Metaheuristic methods created by other researchers, such as genetic algorithms,

simulated annealing, tabu search, and plant propagation, typically suggest a starting point for a problem rather than a feasible solution. A feasible region was previously identified as the set $x: g(x) = b$. A feasible settlement point is one where the set $S = x: g(x) = b$ contains the point x. Assume that the combinatorial optimization issue can be expressed in the following general form:
Maximize: $Z = f(x)$ (P)
Constraint: $g_i(x) = b_i, i = 1, 2, \dots, n; x \in \{0,1\}$
If $f(x)$ and $g_i(x) = b_i, (i = 1, 2, \dots, n)$ is a linear function then the problem (P) can be expressed in the following form:
Maximize: $Z = C^T X$
Constraint: $A_x = b$ (PO)
$x \in \{0,1\}$
binary conditions relax then (OP) can be written:
Maximize: $Z = C^T X$
Constraint: $A_x = b, x \geq 0$ $(P1)$
It is possible to divide a constraint matrix A of size $m \times n$ (m rows, n columns) into a basic matrix (B) of size $m \times n$ and an unbasic matrix (N) of size $m \times (n - m)$ in order to write:

$$A = (BN) \tag{12}$$

It is possible to divide the analog for the vector variable x in accordance with the vector X_B as the basis variable and X_N non-base variable. Now expressions $Ax = b$ become:

$$(BN)\begin{pmatrix} X_B \\ X_N \end{pmatrix} = b \tag{13}$$

Multiply,

$$BX_B + NX_N = b \; atau \; BX_B = b - NX_N \tag{14}$$

This matrix has an inverse element since matrix B is a fundamental matrix (B^{-1}). Multiply from equation's left side (14) by B^{-1} there is:

$$B^{-1}B_{XB} = B^{-1}b - B^{-1}NX_N \tag{15}$$

$IX_B - B^{-1}b - B^{-1}NX_N$ with I unit matrix. So,

$$XB = B^{-1}b - B^{-1}NXN \tag{16}$$

Value X_n is 0, from the non-negative condition $x \leq 0$, obtaining a workable settlement point for (PL):

$$X_b = \beta \; with \; \beta - B^{-1}b \tag{17}$$

3.2. Optimization testing

After the feasible point has been obtained from the $X_b = \beta \; with \; \beta - B^{-1}b$ this point needs to be tested whether it is optimal for the problem (PL). From the point of view of the objective function (PL): $Z = C^T X$. Vector C and x partitioned according to the matrix base (B) and no base (N):

$$SoZ = (C_B \; C_N)\begin{matrix} X_B \\ X_N \end{matrix} \tag{18}$$

Constraint, obtained:

$$Z = C_B X_B + C_N X_N \tag{19}$$

Substitute (16) for X_B, obtained produce maximum resolution. However, if $Zj - Ci \geq 0$, then vector X_N. X_N is increased from the limit of 0 which will result in the Z value decreasing (shrink) or staying the same, meaning that the X_B point that has been obtained is already the maximum point, therefore the maximum condition for the problem (PL) has been obtained, namely:

$$Zj - Cj \geq 0 \forall j \; (non \; basis) \tag{20}$$

Point worth to CO.

$$Z = C_B\,(B^{-1}\,b - B^{-1}\,N\,X_N) + C_N\,X_N \tag{21}$$

$$Z = C_B\,B^{-1}\,b - C_B B^{-1}\,N\,X_N + C_N\,X_N \tag{22}$$

$$Z = C_B\,B^{-1}\,b - (C_B B^{-1}\,N - C_N) + X_N \tag{23}$$

Supposing:

$$Zj = C_B B^{-1} N, \forall j \in \tag{24}$$

So, $Zj - Cj = C_B B^{-1} N - C_N, \forall j \in$. If $Zj - Cj < 0$ (negative) and the set of vectors X_N is increased from the limit of 0, it turns out that Z will rise for the problem (PL), which implies that the objective function's value can still increase. So, in other words that point X_B which has been obtained yet note that point values are feasible X_B stated by (17) is for the problem (PL). Now look at the problem (PO) constraint $x \in \{0,1\}$ can be stated in the form of $x \geq 0; x \leq 1$, So the problem (PO) can be written as:
Maximum $Z = C^T X$
Constrain $Ax = b, x \geq 0; x \leq 1$
Looks like a problem (PL), the possible point value is also expressed as an (6), namely:

$$X_B = B^{-1}b - B^{-1}NX_N$$
$$X_B = \beta - \alpha X_N \tag{25}$$

With $\beta = B^{-1}b\ and\ \alpha = B^{-1}NX_N$.

If the problem (PL) X_N is worth 0 because $x \geq 0$. Alternatively, the worth of the largest variable X_N is at its boundary point which is 0. In combinatorial problems (POL) there are $x \geq 0; x \leq 1$. So in this case the value of the baseless variable X_N is either 0 or 1 , consider the equation again.

$$B^{-1}BX_B = B^{-1}b - B^{-1}NX_N$$
$$IX_B - B^{-1}NX_N \tag{26}$$

It can be seen that the value of the variable base X_N has a value of 0 or 1, meaning that the binary is X_N's value. A plausible solution to the problem (PO) has been found if all of the vector's components have values of 0 or 1. The absence of a workable solution to the issue (PO) is indicated by components of the vector that are not 0 or 1 obtained. The following steps are taken in order to obtain binary values:

a. Isolate a list of fundamental variables I_1 be a set I_2, the variable is a basis that is in its constraints 0 or 1 and the set I_1 in the set I_2, I_3, I_3 .
b. Perform a search by using the goal function to apply the non-basic variable that was kept I_1 and only discrete modifications to the set's variables' values I_2.
c. At the settlement obtained in step 2, check the value $Z_j - C_j$ from the (23) to the variables in the set I_1. If something is moveable from its constraints, add it to the set I_2, repeat from step by step if not stop. As a result of the aforementioned process, every element of the vector β has a binary value, allowing for the creation of a binary viable solution (PO).

Based on the discussion, this research produces a model for optimizing the transportation routes of heterogeneous electric-fueled freight fleets. Determining and determining transportation routes based on refuelling stations using the heterogeneous vehicle routing problem model on transport fleets can produce dynamic new models. This electric heterogeneous vehicle routing problem (EHVRP) model is used to minimize the total travel distance. When the total travel distance decreases, the transportation costs will also decrease. So that will have an impact on the price of goods.

4. CONCLUSION

Based on the results of the study it can be concluded that researchers have produced a model to optimize transportation routes for heterogeneous electric freight fleets. Determining and determining transportation routes based on refueling stations using the HVRP model in the transport fleet can produce a dynamic new model. This HVRP model is used to minimize the total travel distance. When the total travel distance decreases, transportation costs will also decrease, impacting the price of goods.

This study suggests that the geographical conditions used are still using flat road geographical conditions. On flat road geographical conditions, battery consumption is more stable. In the future, the model can be developed by adding other variables according to the geographical conditions of the road, such as the geography of upland roads and congested road conditions. In this research, the charging scenario is applied by replacing the battery at the charging station. In the future, the model can be developed with a direct recharging method at the charging station by paying attention to the charging queue and electric charging times. The model in this study can be produced by applying artificial intelligence, for example, by implementing a genetic algorithm that develops artificial intelligence. An algorithm can be derived and implemented from the resulting model with a programming language such as Python.

REFERENCES

[1] S. R. Andani, M. Zarlis, H. Mawenakana, and S. Sutarman, "Vehicle Routing Problem in Electric Fleet," *2022 4th International Conference on Cybernetics and Intelligent System (ICORIS)*, 2022, pp. 1-4, doi: 10.1109/ICORIS56080.2022.10031546.

[2] N. M. E. Normasari and N. Lathifah, "Heterogeneous Fleet Green Vehicle Routing Problem: A Literature Review," *Angkasa Jurnal Ilmiah Bidang Teknologi*, vol. 13, no. 1, pp. 49–57, 2021.

[3] M. Schneider, A. Stenger, and D. Goeke, "The Electric Vehicle-Routing Problem with Time Windows and Recharging Stations," *Transportation Science*, vol. 48, no. 4, pp. 500-520, 2014, doi: 10.1287/trsc.2013.0490.

[4] J. C. Molina, I. Eguia, J. Racero, and F. Guerrero, "Multi-objective Vehicle Routing Problem with Cost and Emission Functions," *Procedia - Social and Behavioral Sciences*, vol. 160, pp. 254–263, 2014, doi: 10.1016/j.sbspro.2014.12.137.

[5] W. Qin, Z. Zhuang, Z. Huang, and H. Huang, "A novel reinforcement learning-based hyper-heuristic for heterogeneous vehicle routing problem," *Computers & Industrial Engineering*, vol. 156, 2021, doi: 10.1016/j.cie.2021.107252.

[6] J. Szymon and Z. Dominik, "Solving multi-criteria vehicle routing problem by parallel tabu search on GPU," *Procedia Computer Science*, vol. 18, pp. 2529–2532, 2013, doi: 10.1016/j.procs.2013.05.434.

[7] H. Mawengkang and Sutarman, "Generalized Reduced Gradient Approach for Solving Periodic Heterogeneous Vehicle Routing Problem with Side Constraints," *Journal of Physics: Conference Series, International Conference on Advanced Information Scientific Development (ICAISD)*, 2020, vol. 1641, doi: 10.1088/1742-6596/1641/1/012045.

[8] A. Lubis and H. Mawengkang, "A capacitated heterogeneous vehicle routing problem for pharmaceutical products delivery," *Systematic Reviews in Pharmacy*, vol. 11, no. 4, pp. 738–741, 2020.

[9] S. Yang, L. Ning, L. C. Tong, and P. Shang, "Optimizing electric vehicle routing problems with mixed backhauls and recharging strategies in multi-dimensional representation network," *Expert Systems with Applications*, vol. 176, 2021, doi: 10.1016/j.eswa.2021.114804.

[10] *Sources of Greenhouse Gas Emissions*, United States Environmental Protection Agency, 2023. [Online]. Available: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

[11] *Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions, A European Strategy for Low Emission Mobility*, European Commission, 2016. [Online]. Available: https://www.politico.eu/wp-content/uploads/2016/07/Transport-Paper.pdf

[12] Y. Zhou, J. Huang, J. Shi, R. Wang, and K. Huang, "The electric vehicle routing problem with partial recharge and vehicle recycling," *Complex & Intelligent Systems*, vol. 7, pp. 1445–1458, 2021, doi: 10.1007/s40747-021-00291-3.

[13] C. Hecht, K. Victor, S. Zurmühlen, and D. U. Sauer, "Electric vehicle route planning using real-world charging infrastructure in Germany," *eTransportation*, vol. 10, 2021, doi: 10.1016/j.etran.2021.100143.

[14] S. Ou *et al*., *A Study of China's Explosive Growth in the Plug-in Electric Vehicle Market*, Oak Ridge, TN 37831: Oak Ridge National Laboratory, US Department of Energy, 2017. [Online]. Available: https://info.ornl.gov/sites/publications/files/Pub72210.pdf

[15] *Indonesia Transport Policy*, TransportPolicy.net, 2021. [Online]. Availabe : https://www.transportpolicy.net/region/asia/indonesia/

[16] S. Souley, K. Gillet, G. Colin, A. Simon, C. Nouillant, and Y. Chamaillard, "Optimization of the travel time of an electric vehicle with consideration of the recharging terminals," *IFAC-PapersOnLine*, vol. 54, no. 2, pp. 121–126, 2021, doi: 10.1016/j.ifacol.2021.06.017.

[17] M. Keskin, G. Laporte, and B. Çatay, "Electric Vehicle Routing Problem with Time-Dependent Waiting Times at Recharging Stations," *Computers & Operations Research*, vol. 107, pp. 77–94, 2019, doi: 10.1016/j.cor.2019.02.014.

[18] H. Park and S. Jin, "Electric Vehicle Routing Problem with Heterogeneous Vehicles and Partial Charge," *International Journal of Industrial Engineering and Management*, vol. 11, no. 4, pp. 215–225, 2020.

[19] J. Neubauer and E. Wood, "The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility," *Journal Power Sources*, vol. 257, pp. 12–20, 2014, doi: 10.1016/j.jpowsour.2014.01.075.

[20] S. Schoenberg and F. Dressler, "Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles," *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, 2019, pp. 3068-3075, doi: 10.1109/ITSC.2019.8917335.

[21] D. Karyza, "Indonesian EV early adopters face long road ahead," *The Jakarta Post*, 2023.

[22] P. G. Bhwana, "PLN Focusing on Setting Up Electric Vehicle Charging Station Infrastructures," 2023.

[23] S. Zhang, Y. Gajpal, and S. S. Appadoo, "A meta-heuristic for capacitated green vehicle routing problem," *Annals of Operations Research*, vol. 269, pp. 753–771, 2018, doi: 10.1007/s10479-017-2567-3.

[24] M. G. -Echeverri, L. Cubides, and J. O. Bustamante, "The electric vehicle routing problem with backhauls," *International Journal of Industrial Engineering Computations*, vol. 11, pp. 131–152, 2020, doi: 10.5267/j.ijiec.2019.6.001.

[25] Á. Felipe, M. T. Ortuño, G. Righini, and G. Tirado, "A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges," *Transportation Research Part E: Logistics and Transportation Review*, vol. 71, pp. 111–128, 2014, doi: 10.1016/j.tre.2014.09.003.

[26] J. Lin, W. Zhou, and O. Wolfson, "Electric vehicle routing problem," *Transportation Research Procedia*, vol. 12, pp. 508–521, 2016, doi: 10.1016/j.trpro.2016.02.007.

[27] S. Shao, W. Guan, and J. Bi, "Electric vehicle-routing problem with charging demands and energy consumption," *IET Intellegent Transpport System*, vol. 12, no. 3, pp. 202–212, 2018, doi: 10.1049/iet-its.2017.0008.

[28] S. Zhang, Y. Gajpal, S. S. Appadoo, and M. M. S. Abdulkader, "Electric vehicle routing problem with recharging stations for minimizing energy consumption," *International Journal of Production Economics*, vol. 203, pp. 404–413, 2018, doi: 10.1016/j.ijpe.2018.07.016.

[29] S. Ropke and D. Pisinger, "An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows," *Transportation Science*, vol. 40, no. 4, pp. 393-546, 2006, doi: 10.1287/trsc.1050.0135.

[30] Y. Li, H. Soleimani, and M. Zohal, "An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives," *Journal of Cleaner Production*, vol. 227, pp. 1161–1172, 2019, doi: 10.1016/j.jclepro.2019.03.185.

[31] S. Pelletier, O. Jabali, and G. Laporte, "The electric vehicle routing problem with energy consumption uncertainty,"

Transportation Research Part B: Methodological, vol. 126, pp. 225–255, 2019, doi: 10.1016/j.trb.2019.06.006.
[32] A. Boudallaa, M. Chennani, D. Belkhayat, and K. Rhofir, "Vector Control of Asynchronous Motor of Drive Train Using Speed Controller H∞," *Emerging Scince Journal*, vol. 6, no. 4, 2022, doi: 10.28991/ESJ-2022-06-04-012.
[33] A. D. Gorbunova and I. A. Anisimov, "Assessment of the use of renewable energy sources for the charging infrastructure of electric vehicles," *Emerging Scince Journal*, vol. 4, no. 6, 2020, doi: 10.28991/ESJ-2020-01251.
[34] H. Kapeller, D. Dvorak, and D. Šimić, "Improvement and Investigation of the Requirements for Electric Vehicles by the use of HVAC Modeling," *HighTech Innovation Journal*, vol. 2, no. 1, 2021, doi: 10.28991/HIJ-2021-02-01-07.
[35] A. Montoya, C. Guéret, J. E. Mendoza, and J. G. Villegas, "The electric vehicle routing problem with nonlinear charging function," *Transportation Research Part B: Methodological*, vol. 103, pp. 87–110, 2017, doi: 10.1016/j.trb.2017.02.004.

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