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Improvement of Solution Using Local Search Operators on the Multi-Trip Electric Vehicle Routing Problem Backhaul with Time Window

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Abstract: In order to reduce greenhouse gas emissions, logistics companies are strongly encouraged to make their operations more environmentally friendly through efficient solutions by implementing electric vehicles (EVs). However, the driving range is one of the aspects that restricts the introduction of EVs in logistics fleets as it poses new challenges in designing distribution routes. In this regard, this paper investigates the issue of the Electric Vehicle Routing Problem (EVRP) raised by logistics companies in real time. There are many models that extend the classic VRP model to consider electric vehicles, but VRP by combining the features of capacity VRP, VRP with time window, backhaul VRP, multi-trip VRP, and electric VRP (MT-EVRPBTW) has not been worked out yet. We present a mathematical model of the MT-EVRPBTW to explain the problem in detail with the objective function to minimize the total distance travelled, where each vehicle could be charged nightly at the depot and during the day at the rest time of the driver in the depot. A feasible initial solution is built using a constructive heuristic to solve this problem, namely, the sequential insertion heuristic, which will be done by improving the solution using Local Search operators. Several Local Search processes using inter-route and intra-route operators for improvement solutions are tested and compared to their performance in measuring the impact of Local Search operator usage on overall travelled distance. Computational experiments for five Local Search operators will be presented and analyzed based on data from one of Indonesia's post and parcel companies.

Keywords: Electric vehicle routing problem, Backhauls, Multiple trips, Time window, Local search operator

Introduction

Under the 2015 Paris Agreement, Indonesia must reduce 30% of GHG emissions by 2035 (Indonesian Minister of Industry Regulation Number 27, 2020). However, Indonesia ranks fourth as the highest carbon-emitting country in the world (World Bank, 2020). The transportation sector is responsible for emitting large amounts of CO2. Emissions generated from the transportation sector are 157,326 Gg CO2e, with an average increase in emissions of 7.17% per year (ESDM, 2019). In addition, freight vehicle contributes to most of this emission growth. The procurement of freight vehicles continues to increase by 4.7% per year, accompanied by an increase in post and logistics services.

Reducing emissions produced by the logistics sector is important to create an environmentally friendly logistics system. Furthermore, emissions reduction can enhance the overall effectiveness and efficiency of the logistics network (Indonesian Ministry of Energy and Mineral Resources, 2019). One strategy to reduce emissions produced by the logistics sector is implementing policies to use more energy-efficient vehicles such as, electric vehicles (Aziz and Abidin, 2021). EV vehicles are considered more environmentally friendly and to have a great potential to reduce GHG emissions from transportation (Tang et al., 2022; Pan et al., 2023). In light of the growing emphasis on environmental sustainability and improved quality of life, logistics service providers in various countries have initiated fuel-switching strategies for their freight vehicles (Muñoz et al., 2019). Several leading logistics service providers have switched to electric vehicles, including FedEx, UPS, and DHL (Ehrler et al., 2021).

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The transition to electric vehicles in Indonesia is supported by the transformation policy that regulates battery-powered electric motor vehicles used in road transportation, as stated in Presidential Regulation No. 55 of 2019. This policy is designed to stimulate the rapid advancement of battery-based electric motor vehicles in road transportation. Its primary objectives are to enhance energy efficiency, promote energy conservation within the transportation sector, and contribute to adopting clean energy sources. Moreover, this policy aligns with Indonesia's commitment to reduce greenhouse gas emissions and fosters cleaner and more environmentally friendly air quality. However, the EV implementation in logistics service providers is facing significant mileage and recharge time limitations. Given these challenges, companies need efficient route planning techniques by considering the characteristics of electric vehicles. The routing approaches for conventional vehicles do not apply to electric vehicles, which leads to a new optimization problem called the Electric Vehicle Routing Problem (EVRP).

A basic EVRP is usually a series of routes to reach a specific destination function that serves all customer demands while considering the fulfilment of mileage restrictions and electric vehicle recharging requirements. Therefore, a real-world EVRP study that considers the operating issues of postal and parcel delivery companies in Indonesia is presented in this paper. Driven by the challenges mentioned earlier, postal and parcel delivery companies decided to change their vehicle fleet from fuel-powered vehicles to electric vehicles. In this case, a homogeneous vehicle departs from the depot to deliver the customer's package first until the vehicle's load is empty and then picks up the package. The policy can be called backhauling: all delivery operations are restricted to being carried out before the pick-up operation. The vehicle can return to the depot more than once to unload the collected package and load the parcel to be delivered. A full recharge can be performed if the service tour cannot be completed due to insufficient vehicle energy levels. However, drivers spend rest time at the depot, so the company focuses on having vehicle recharging stations used during drivers' rest periods. The goal is to minimize the overall distance travelled by vehicle. So, the problem is addressed by combining the variant VRP capacity (Toth and Vigo, 2002), VRP with time window (Braysy and Gendreau, 2007), VRP multi-trip (Taillard et al.,1996), VRP backhaul (Goetschalckx and Jacobs, 1989) and EVRP with charging station (Nolz et al., 2022).

Many studies have discussed VRP variants using electric vehicles (EVRP) before. However, to the best of the researchers' knowledge, studies discussing the merging of route problems with backhaul variants and multi-trip with time windows using electric vehicles (MT-EVRPBTW) have never been conducted. As stated by Zhang and Zhang (2022) in their research review literature, there are still few studies that discuss the MT-EVRP problem. Kucukoglu et al. (2021), in conducting a comprehensive study in which there are 136 references to variants of the Electric Vehicle Routing Problem (EVRP), two researchers were found to discuss the Electric Vehicle Routing Problem Backhaul (EVRPB), namely Echeverri et al. (2020) and Cubides et al. (2019). The EVRPB research has not considered the existence of multi trips in the depot to carry out the unloading and loading process more than once.

Since the EVRP is classified as an NP-hard combinatorial optimization problem, finding an optimal solution within a reasonable time is challenging. There have been several methods in recent years that offer potential solutions. The exact algorithms, such as branch-and bound, are recognized as the most straightforward method for deriving the optimal solution. However, due to their high computational complexity, exact algorithms are only practical for small-scale problems (Garey and Johnson, 1979). To address this limitation, the heuristic algorithms that rely on thumb, intuition, and experience are proposed as an alternative for quickly finding good solutions (Tang et al., 2023). In the last decade, many successful heuristic algorithms have been developed to solve instances of several hundred customers to near-optimal solutions within minutes of computational time (Vidal et al., 2013). Most heuristics are based on metaheuristic designs. Many authors have shown that metaheuristics have high-quality results that can be achieved with different designs (However, one component that all good heuristics for EVRP may have in common is Local Search (Arnold and Sörensen, 2019).

Local Search (LS) has been established as a successful cornerstone for addressing EVRP and is included in many advanced heuristics. This paper aims to show that a well-implemented Local Search is enough to create heuristics that compute high-quality solutions quickly. To fill the gap of the EVRP variant, this paper first adapts MT-EVRPBTW drawn from real-world cases. Then, five commonly used LS operators, namely Shift (1,0), Swap (1,1), Swap (2,2), Relocation, and Reinsert, were used to solve the MT-EVRPBTW problem to investigate the influence of five LS operators in finding promising solutions for MT-EVRPBTW.

The rest of the study is structured as follows. Section 2 provides a brief review of the pertinent literature about the EVRP. Next, Section 3 establishes a mathematical model of the problem being studied. Section 4 describes the Local Search operators we used in this study. We define these operators with illustrations and describe the initial solution (Sequential Insertion Heuristic) used. Section 5 presents the results of tests conducted with these operators. Finally, Section 6 concludes the study and discusses future work.

Related Works

VRP was first proposed by Dantzig and Ramser (1959). Many studies have developed VRP variants for several applications. MTVRP is one variant that extends the classic VRP by adding some restrictions. It has a set of vehicles and drivers working on several routes or trips in a certain period. MTVRP was first introduced by Fleischmann (1990). Furthermore, MT-VRP considering the time window, was addressed in Azi, Gendreau, and Potvin (2007). They formulated it as an integer programming model with a weighted sum of two conflicting objectives, i.e., maximization of total revenue and minimization of total distance, and solved it by using brunch and price. Extending from MT-VRPTW, Neiraa (2020) learned Two-İnteger Programmings (IP) models for multi-trip vehicle routing problems with time windows, service-dependent loading times, and limited trip duration (MTVRPTW-SDLT). Huang (2021) introduces a multi-trip vehicle routing problem variant with a time window on urban garbage collection, where vehicles must wait in queues after the unloading capacity is filled. To complete the model, they proposed a Branch-And-Price-And-Cut Algorithm (BPC). Recently, Chena et al. (2023) investigated route planning for cold supply chain distribution of fresh food companies. They address route issues considering time windows, multiple trips per vehicle, heterogeneous fleets, parking constraints, loading and unloading times at customer positions, and limited duration to minimize associated operational costs. They formulated this problem as a Mixed-İnteger Programming mode.

The VRPB is also an extension of the classical VRP. Further constraints include vehicles delivering to all the linehaul customers before visiting any backhaul customers. Koc and Laporte (2018) conducted a comprehensive literature study on VPRB, including variants of VRPB, heuristic, and metaheuristic approaches to complete VRPB applications. For example, Chavez et al. (2016) proposed a Pareto Ant Colony Algorithm to solve a multi-objective variant of Multi-Depot VRPB where the goal is to minimize distance, travel time, and energy consumption. Bajegani et al. (2021) present a mathematical model for a single depot, time-dependent vehicle routing problem with backhaul considering the First İn First Out (FIFO) assumption. Their proposed Variable Neighborhood Search (VNS) meta-heuristic and mat-heuristic algorithms have been designed that were applied to the real case study in the post office of Khomeini-Shahr town, Iran, and resulted in a reduction in vehicle travel time.

However, little literature is available on the MTVRPB, and the company needs to visit the transfer stations on multiple rounds daily for package delivery and pickup, where each round is called a batch. Ong dan Suprayogi (2011) developed the new VRP variants: VRP with backhauls, multiple trips, and time window (VRPBMTTW), that solved Ant Colony Optimization (ACO) and Sequential Insertion as the initial solution algorithm, minimizing the number of vehicles, the total duration time and the range of duration times. Wassan et al. (2017) presented the MTVRPB with a homogenous fleet by filing ILPs for small and medium-sized instances to minimize the total cost by reducing the total distance travelled and the suitable number of vehicles used. Meanwhile, a metaheuristic VNS two-level variable neighborhood search algorithm was employed for large instances. Sethanan and Jamrus (2020) examined MTVRPB for beverage distribution with a heterogeneous fleet that uses glass bottles for soft drinks to deliver to all customers who need soft drinks in glass bottles before making any pickups of empty glass bottles from clients to return to the Depot. This study aimed at both an integer linear programming formulation and a novel hybrid differential evolution algorithm involving a genetic operator with a fuzzy logic controller whose objective function is to minimize total cost related to distance travelled.

In recent years, there have been more and more studies on EVRP due to increasing social concern over low carbon consumption and environmental sustainability. EVRP is an expansion of VRP where the vehicles use electric vehicles. EVRP was first introduced by Conrad and Figliozzi (2011), where electric vehicles can recharge at a fixed customer location to extend their trip. Then Schneider et al. (2014) introduced EVRPTW with full vehicle recharging based on a linear charging function.

Research on the expansion of VRPB using electric vehicles (EVRPB) was conducted by Cubides et al. (2019), which is formulated as a mixed-integer linear programming model that considers the operation of the DN in conditions of maximum power demand. This problem is formulated by adopting a multi-objective approach where transportation and the operation of power distribution networks are modelled. The study considered recharging electric vehicle batteries at the end of linehaul or during backhaul routes. Granada et al. (2020)

examined the Electric Vehicle Routing Problem with Backhauls (EVRPB) to minimize two operating costs. The first is the total cost of the travel route used for shipping and picking up goods, and the second is the cost of the travel route to the recharging station. The solution method uses the exact method of Mixed Integer Linear Programming (MILP), which can produce solutions quickly and effectively. Nolz et al. (2022) researched EVRPB by adding time window limits for each customer and consistency of customer visit time. The recharging point is based on the end of the linehaul service route within the depot during the break time. The settlement method uses the Adaptive Large Neighborhood Search (ALNS) method in a case study at an Austrian parcel delivery company.

Research on the expansion of MT-VRP using electric vehicles (MT-EVRP) was conducted by Zhang and Zhang (2022) regarding electric buses that pick up where vehicles have more than one route. The solution to these problems used genetic algorithms with an improved recombination strategy (GA-IR). Wang et al. (2023) combined multi-trip EVRP with a heterogeneous fleet with the objective function of this study, which is to minimize the total mileage time and total fixed costs of electric vehicles by using the Hybrid LNS method using benchmark data from previous studies. Zhao and Lu (2019) combined various variants by considering time windows, heterogeneous fleets, and multi-trip (MT-EVRPHFTW). The model is applied to logistics companies in Wuhan to minimize the total cost of total mileage and recharge costs completed using the Adaptive Large Neighborhood Search (ALNS) method.

Studies that examine VRP with Multi-trip, backhaul, and time window (MT-VRPBTW) are still limited. At the same time, MT-VRPBTW, which uses electric vehicles with recharging (MT-EVRPBTW), has yet to be worked out. Therefore, this study proposes an MT-EVRPBTW that integrates EVRP with multi-trip, backhaul and time window that considers mileage with energy consumption.

Proposed Model for the EVRPB

Problem Description

In MT-EVRPBTW, the central depot has two types of customers served, namely customers with linehaul requests and customers with pick-up requests. Linehaul customers must be served first before serving backhaul customers. Vehicles can return to the depot more than once to carry out the unloading of goods and also the loading process, which is the filling of the cargo of goods. The depot is also used by drivers as a place to rest until the next departure. In the VRP variant with electric vehicles (EVRP), the vehicle requires recharging to increase driving range. Many researchers assume that electric vehicle batteries are in full state and ready for use in vehicles departing from depots at the beginning of the time horizon. Electric vehicles can recharge if the range cannot perform services during the time horizon. The location of recharging vehicle batteries used in this study is a charging depot. The level of recharge power is assumed to be constant, and this assumption has been widely used by researchers such as Zhang and Zhang (2022), Hierman et al. (2016), Wang et al. (2023), and Nolz et al. (2022).

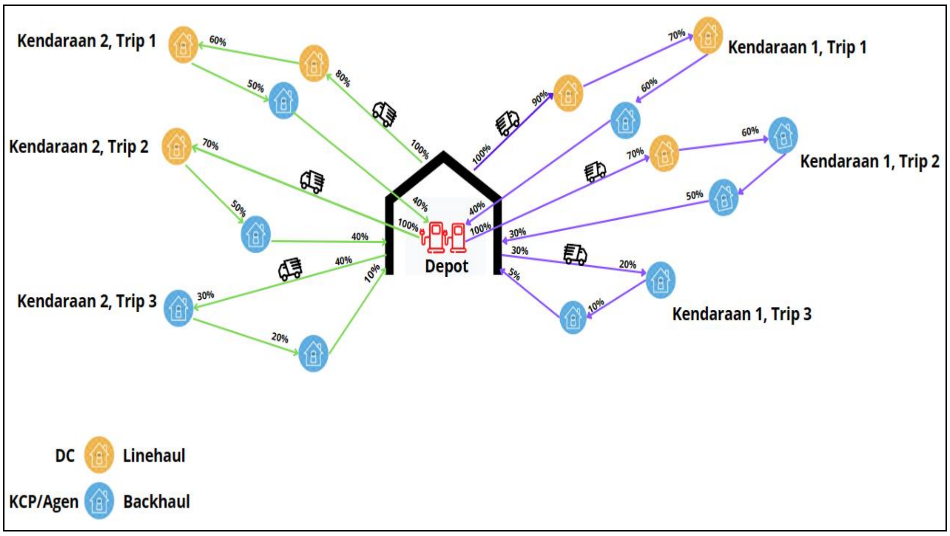

Figure 1. Illustration from MT-EVRPBTW

The strategy used in developing this research model uses a full charging strategy, with a long recharging time that is assumed to be constant. This assumption can be found in various studies such as Zhao and Lu (2019), Afroditi et al. (2014), and Erdogan and Miller (2012). The energy consumption used in this study is linear with the distance travelled. This assumption is widely used in EVRP problems by many researchers, such as Zhang and Zhang (2022), Nolz et al. (2022), Keskin and Çatay (2016), Schiffer and Walther (2017), Erdelić et al. (2019). Customers served have a time window, and vehicles are not allowed to arrive before the specified service time. An illustration of the system can be seen in Figure 1 above.

Table 1. Notation and decision variables

	Notation
I	The set of nodes, $I = V \cup C \cup \{0, n+1\}$, V is the customer node, C the charging station, 0 the initial depot and $n+1$ the final depot
A	Arc set $A = \{((i,j)\|i,j \in I, i \neq j)\}$
V	The set of customers, $V = L \cup B$, where the linehaul customers $L = \{l_1, l_2, \dots, l_{n+1}\}$ and backhaul customers are $B = \{b_1, b_2, \dots, b_{n+1}\}$.
N'	The set of recharge points where refilling takes place at a depot, $N' = \{C, n+1\}$
K	The set of electric vehiclee, $\{k_1, k_2, \dots, k_{n+1}\}$
U	The set of trips, $\{u_1, u_{2,}, , u_n\}$
a_i	The earliest time of receipt of service to customers i
b_i	The latest time of receipt of service to customers i
a_{rech}	Earliest start time of recharge
b_{rech}	The latest start time of recharge
c_{ij}	Travel time between nodes i and j
w_{ik}^u	Dwell time is the waiting time for the vehicle at the final depot on the trip u
T_{li}	Service time for customers L
T_{bi}	Service time for customers B
T_{ni}	Service time in the depot
T_{ck}^u	Electric vehicle recharging time
v_k	Time to start recharging the energy of vehicle k
w_k	The end time of recharging the energy of vehicle k
q_i	The number of requests for customers i, which i is based on the type of customer, namely L if the delivery request, and B if pick-up requests
E	Electric vehicle battery capacity
G	Recharging power level
d_{ij}	The distance between points on the arc (i,j)
pm_E	Energy consumption per kilometer
s	Vehicle speed
Q_i	Maximum capacity of vehicles for customers i
M	The value of the large constant
	Decision Variables:
x_{ijk}^u	A binary variable that has a value of 1 if the arc (i,j) is traversed by a vehicle during the trip u and a value of 0 otherwise
y_{ik}^u	A binary variable that has a value of 1 if the vehicle k visits a point i along the trip u and a value of 0 otherwise
t_{ik}^u	Time of the vehicle k when visiting points i along the trip u, $t_{ijk}^u \geq 1$
e_{ik}^u	Remaining energy of vehicle k when visiting points i on a trip u, $e_{ijk}^u \geq 1$
e_{ck}^u	Additional energy of vehicle k when recharging at a recharging station on a trip u, $e_{ijk}^u \geq 1$

In the formulation of the MT-EVRPBTW mathematical model, there is one depot and n customers that must be served. The problem can be described as a complete directed graph $G = (I, A)$, where $I = V \cup C \cup \{0, n+1\}$. V is a node or customer point which $V = L \cup B$ consists of linehaul customers $L = \{l_1, l_2, \dots, l_{n+1}\}$ and backhaul customers $B = \{b_1, b_2, \dots, b_{n+1}\}$. 0 is the initial depot as the departure of the vehicle to start a trip, and the final depot $n+1$ is the place of return of the vehicle after a trip is completed. The set $N' = C\ U\ n+1$ is a depot that can be used to make multi trips as well as for recharging vehicle C. The set $A = \{((i,j)|\text{i,j} \in I, i \neq j)\}$ is the set of arcs.

Each customer V has a service request q_i that is not allowed to exceed the maximum capacity Q_i. Homogeneous vehicles $k \in K$ travel distances d_{ij} with as much travel time c_{ij} and have a constant speed s to make a trip $u \in U$. Service time in carrying out service activities such as loading or unloading is divided into three, namely, service time for linehaul customers amounting to T_{li}, service time for backhaul customers amounting to T_{bi}, and service time in the depot amounting to T_{ni}, assuming that the service time on each node is constant. Each customer must be served within their respective time window ranges with a start time a_i and an end time b_i. Vehicles that have finished the service in the depot but the initial time window for customers has not been opened, then the vehicle must wait inside the depot with a waiting time w^u_{n+1k} before departing again.

The vehicle has a battery capacity E with battery energy consumption per kilometer pm_E. Energy consumption is assumed to be linear with mileage. If the battery energy contained in the vehicle is insufficient to cover a route, then the vehicle needs to recharge the battery during the recharge time T^u_{ck} and with the recharge power level G. Recharging is done in the depot during rest periods that have a period $[a_{rech,} b_{rech}]$. Related notations are summarized in Table 1.

Mathematical Formulation

We propose a mathematical formulation for the MT-EVRPBTW inspired by Zhang and Zhang (2022) with their research MT-EVRPTW with the addition of the following constraints:

$$Min \sum_{(1,j)\in A} d_{ij} \sum_{k\in K} \sum_{u \in U} x^u_{ijk} \qquad (1)$$

Subject to:

[Route selection constraints]

$$\sum_{j\in V\cup N'} x^u_{ijk} = \sum_{j\in 0\ \cup V} x^u_{ijk} = y^u_{ik} \qquad \forall i \in V, k \in K, u \in U \qquad (2)$$

$$\sum_{j\in V\cup C} x^u_{0jk} = \sum_{j\in V} x^u_{jn+1k} \qquad \forall k \in K, u \in U \qquad (3)$$

$$\sum_{j\in V} x^u_{jN'} \leq 1 \qquad \forall k \in K, u \in U \qquad (4)$$

$$\sum_{k\in K} \sum_{u\in U} y^u_{ik} = 1 \qquad \forall i \in V \qquad (5)$$

$$\sum_{k\in K} \sum_{u\in U} y^u_{ik} \leq 1 \qquad \forall i \in C \qquad (6)$$

$$x^u_{ijk} = 0 \qquad \forall i \in B, j \in L \qquad (7)$$

$$x^u_{iN'} = 0 \qquad \forall i \in L \qquad (8)$$

[Time constraints]

$$a_i y^u_{ik} \leq a_i y^u_{ik} \leq t^u_{ik} \leq b_i y^u_{ik} \qquad \forall i \in V \cup \in K, u \in U \qquad (9)$$

$$t^u_{ik} + T_{li} + c_{ij} \leq t^u_{jk} + M\left(1 - x^u_{ijk}\right) \qquad \forall i \in L, j \in V, k \in K, u \in U \qquad (10)$$

$$t_{ik}^{u} + T_{bi} + c_{ij} \leq t_{jk}^{u} + M\left(1 - x_{ijk}^{u}\right) \qquad \forall i \in B, j \in B, k \in K, u \in U \tag{11}$$

$$a_i y_{ik}^{u} \leq t_{ik}^{u} + T_{n0} + c_{ij} \leq t_{jk}^{u} + M\left(1 - x_{ijk}^{u}\right) \qquad \forall i \in \{0\} \in V, k \in K, u \in U \tag{12}$$

$$a_i y_{ik}^{u} \leq t_{ik}^{u} + T_{bi} + c_{in+1} \leq t_{n+1k}^{u} + M(1 - x_{in+1k}^{u}) \qquad \forall i \in B, k \in K, u \in U \tag{13}$$

$$t_{ik}^{u} \leq b_{rech}\, y_{ik}^{u} \qquad \forall i \in C\; k \in K, u \in U \tag{14}$$

$$a_{rech}\, y_{ik}^{u} \leq\; t_{ik}^{u+1} + T_{n0} \qquad \forall i \in C \in K, u \in U \tag{15}$$

$$T_{ck}^{u} = \frac{E - e_{ik}^{u}}{G} \qquad \forall\, k \in K \tag{16}$$

$$a_i y_{ik}^{u} \leq t_{ik}^{u} + T_0 \; + T_{cik}^{u} + c_{ij} \leq t_{jk}^{u} + M\left(1 - x_{ijk}^{u}\right) \qquad \forall i \in C, j \in V, k \in K, u \in U \tag{17}$$

$$t_{0k}^{u+1} = t_{n+1k}^{u} + T_0 + w_{n+1k}^{u} \qquad \forall k \in K, u \in U \tag{18}$$

$$t_{ck}^{u+1} = t_{ck}^{u} + T_0 + T_{ck}^{u} + w_{ck}^{u} \qquad \forall k \in K, u \in U \tag{19}$$

$$c_{ij} = \frac{d_{ij}}{s} \qquad \forall (i,j) \in A \tag{20}$$

[Remaining power and capacity constraints]

$$e_{ak}^{u} - d_{ij} pm_E \geq e_{jk}^{u} - M\left(1 - x_{ijk}^{u}\right) \qquad \forall i \in C, j \in V, k \in K, u \in U \tag{21}$$

$$e_{ik}^{u} - d_{ij} pm_E \geq e_{jk}^{u} - M\left(1 - x_{ijk}^{u}\right) \quad \forall i \in V \cup \{0\}, j \in V, k \in K, u \in U \tag{22}$$

$$e_{ik}^{u} \geq min\{d_{ij} pm_E + d_{jn+1} pm_E, d_{in+1} pm_E\} \quad \forall i \in V, j \in V, k \in K, u \in U \tag{23}$$

$$e_{0k}^{u+1} = e_{n+1k}^{u} + e_{ck}^{u} y_{ck}^{u} \qquad \forall k \in K, u \in U \tag{24}$$

$$\sum_{i \in L} q_i\, y_{ik}^{u} \leq Q_i \qquad \forall i \in L, k \in K\; u \in U \tag{25}$$

$$\sum q_i\, y_{ik}^{u} \leq Q_i \qquad \forall i \in B, k \in K\; u \in U \tag{26}$$

$$x_{ijk}^{u} \in \{0,1\} \qquad \forall i \in L, j \in L \cup B \cup C \cup \{0\}, k \in K, u \in U \tag{27}$$

$$x_{ijk}^{u} \in \{0,1\} \qquad \forall i \in B, j \in B \cup C \cup \{0 \cup n+1\}, k \in K, u \in U \tag{28}$$

$$y_{ik}^{u} \in \{0,1\} \qquad \forall (i,j) \in A, k \in K, u \in U \tag{29}$$

$$e_{ck}^{u} \geq 0 \qquad \forall i \in I, k \in K, u \in U \tag{30}$$

The objective function [1] is to minimize vehicle mileage. Constrain [2]-[3] represents flow conservation and ensures that vehicles departing from the depot are the same as vehicles arriving back at the depot. Constrain [4] This constraint indicates whether the vehicle will depart back from the final depot or not. The constraint indicates the existence of multi-trip where departure and return at the depot are possible more than once. Constrain [5] indicates that each customer must be visited exactly once by one vehicle on one trip. Constrain [6] limits recharging activities to no more than once. Constraint [7] that ensures that there is a prohibition on vehicles from visiting linehaul customers after visiting backhaul customers. Constrain [8] ensure the prohibition of vehicles from directly visiting the final depot after serving linehaul customers. Constrain [9] states the arrival time at the customer's point to be between the customer's time window intervals $[a_i, b_i]$. Constrain [10] and constrain [11] states the prohibition of the arrival of the vehicle at the customer j before the arrival time of the vehicle at the customer i has finished servicing and traveling from the customer i to the customer j. Where I for linehaul customers [10] and backhaul customers [11]. Constrain [12] states the prohibition of arrival at the customer j before a certain time $(t_{ik}^{u} + T_{n0} + c_{ij})$ if they travel from the depot to the customer j. Constrain [13] states the prohibition of arrival at the customer j before a certain time $(t_{ik}^{u} + T_{bi} + c_{in+1})$ if they travel from the customer j backhaul to the final depot $n+1$. The arrival of the vehicle at the recharging station must be less than the end time of recharge [14]. While the departure time of the vehicle from the recharging station must be more than the initial time of recharging plus the service time [15]. Constraint [16] calculates the recharging time assuming the battery recharging rate G is a constant. Constrain [17] states the prohibition of arrival at the customer j before a certain time $(t_{ik}^{u} + T_0 + T_{cik}^{u} + c_{ij})$ if they perform from the recharge station to the customer j. Constraint [18]-[19] states the time of route sequence, where the departure time of the next trip is equal to the arrival time of the previous trip plus the service time plus the waiting time of the vehicle [18]. While Constrain [19] states the order of route if the departure of the vehicle from the recharging station. Constraint [20] states the relationship between speed and travel time and distance traveled.

Constrain [21] ensures that the vehicle has enough battery energy to travel toward the customer after recharging at the depot recharging station. Constrain [22] ensures that the vehicle has sufficient battery energy to travel to the customer j if the vehicle departs from a depot or another customer i. Constrain [23] ensures that the remaining energy of the vehicle battery must be sufficient when visiting a customer and then directly traveling back to the depot, or the remaining energy must be sufficient when visiting other customers i before returning to the depot. Constrain [24] states that the remaining energy of the vehicle battery when departing from the depot for the next trip is the same as the remaining battery energy upon arrival at the depot on the previous trip plus the additional energy if the vehicle recharges in the depot. A value of y_{ik}^{u} is 1 if the vehicle recharges, and a value of 0 if the vehicle does not recharge. Constrain stating that the number of customer requests carried by a vehicle does not exceed its maximum capacity, constrain [25] for linehaul customers and [26] for backhaul customers. Constraints [27]-[30] specify the types and ranges of the decision variables.

Methodology

Local Search

Local Search (LS) is one of several common approaches to combinatorial optimization problems with empirical success (Johnson et al., 1988). Local Search is a good method for producing quality solutions in completing vehicle routing relatively quickly (Arnold and Sörensen, 2019). The basic idea underlying Local Search is to start with some feasible solution x of the problem; the neighborhood of a Local Search operator is the set of solutions $N(x)$ that can be reached from x by applying a single move of that type. To evaluate it (i.e., calculate the corresponding objective function $f(x)$ and then evaluate $f(y)$ for some feasible solution y, which is a neighborhood of x. If a neighborhood y provided that this solution is better than the current solution $(f(y) < f(x))$ is found, then select y and repeat the same procedure. If no improving solution is found in the neighborhood of the current solution, a local optimum has been reached. In some cases, Local Search provides a near-optimal or even optimal solution quickly (Smet et al., 2016). It is particularly suitable for large instances where the search space is too large to explore in a reasonable amount of time.

In the Local Search process, an operator defines the environment, which is the set of solutions that can be generated by applying the operator to a single solution. A move is a transition from one solution to another in its environment. The success of the Local Search is highly dependent on the surrounding environment and the operators used. In general, Local Search operators for VRP can be distinguished between operators for intra-route optimization and operators for inter-route optimization. These two operator types reflect the two tasks that one has to solve in a VRP: (1) the optimization is carried out on two or more than one different route (inter-route optimization), and (2) the optimization of each route in itself (intra-route optimization). In this paper, we mainly embed five common LS operators widely used for traditional VRP by taking the three intra-route operators found in the research of Subramanian et al. (2010), and two inter-route operators in the research of Silva et al. (2015). Here are some changes in the structure of the neighborhood inter-route and intra-route:

Shifts (1,0)

A node *c* is transferred from route 1 to route 2. In Figure 2b, node 7, which was originally on route 1, was moved to route 2. So, route 1, which originally had 5 nodes (1-2-8-9-10), had 6 nodes (1-2-7-8-9-10), and route 2, which originally had 6 nodes (6-7-11-3-4-5), had 5 nodes (6-11-3-4-5) because node 7 has been moved.

Swap (1,1)

Swap (1,1) was introduced by Boudia et al. (2007); it is a permutation between node c1 from route 1 and node 2 from route 2. In Figure 2c, node c2 from route 1 is swapped with node c6 from route 2. This operation is also known as 1-1 Neighborhood Exchange.

Swap (2,2)

Swap (2,2) has almost the same move as swap (1,1) by moving 2 nodes instead of moving 1 node. The interchange between two adjacent nodes, c1, and c2, from a route 1 by another two adjacent nodes, c3, and c4, belonging to a route 2. The opposite arcs (c2, c1) and (c4, c3) are also considered, yielding 4 possible combinations (Fig 2d- Fig 2g).

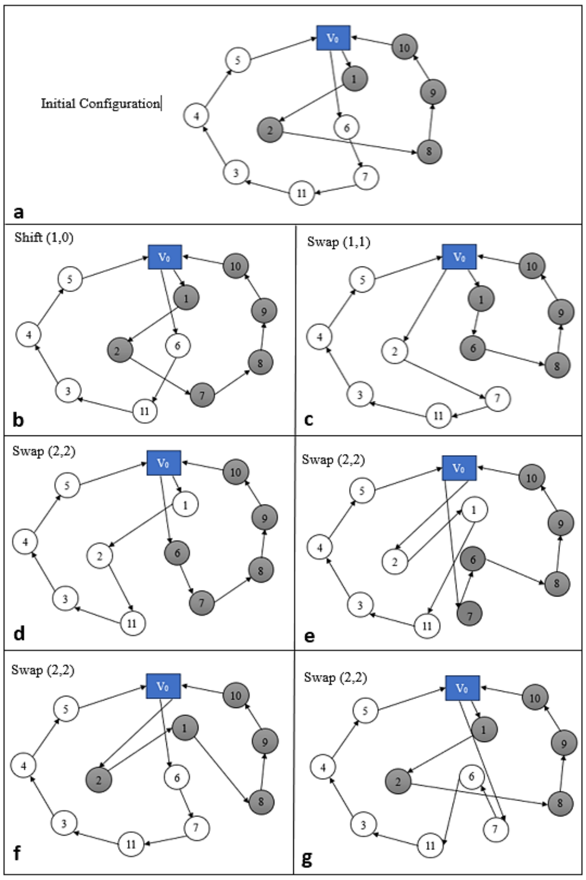

Figure 2. Inter-route neighborhoods.

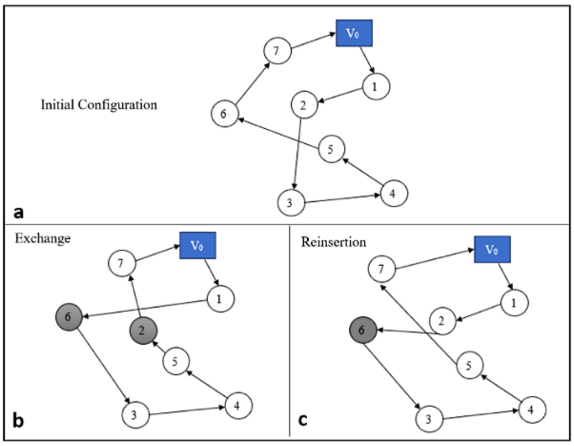

Figure 3. Intra-route neighborhoods.

In Fig. 2d, the adjacent node c6 and c7 were exchanged with the adjacent node c1 and c2. In Fig. 2e, the adjacent node c7 and c6 were exchanged with the adjacent node c2 and c1. In Fig. 2f, the adjacent node c6 and c7 were exchanged with the adjacent node c2 and c1. In Fig. 2g, the adjacent node c7 and c6 were exchanged with the adjacent node c2 and c1. In Fig. 2f, the adjacent node c7 and c6 were exchanged with the adjacent node c1 and c2. Two intra-route neighborhood structures were also implemented. Fig. 3 shows an example of each one of these neighborhood operators. The following two intra-route neighborhood structures were considered:

Exchange

Permutations between two nodes. This Exchange is shaped like Swap (1,1) but is in an intra-route version or occurs in the same route. An example of the Exchange move is shown in In Fig. 3b, that the nodes 2 and 6 were swapped. So that the sequence of nodes which was originally 1-2-3-4-5-6-7 becomes 1-6-3-4-5-2-7.

Reinsertion

One customer in the route is deleted, then the customer is reinserted into a different position on the same route. An example of the Exchange move is shown in In Fig. 3c that node 6 is deleted from the previous sequence and then moved to the sequence after node 2. So, the sequence of nodes which was originally 1-2-3-4-5-6-7 became 1-2-6-3-4-5-7.

All types of movement from the operators above must pay attention to the constraints that have been determined previously, and these constraints may not be violated for each movement. As an example of the capacity of each swap transfer (1,1), where the capacity of node 2 (q_2) from route 1 exchanged with node 6 from route 2 with capacity (q_1) cannot exceed the capacity of vehicle Q Time window limit for each customer $[a_i, b_i]$. may not be violated. The energy consumption (pm_E) at each node movement must not violate the electric vehicle battery capacity E. Rules for backhaul where nodes with shipping customers are always served first before nodes with pickup services.

Initial Solution

Based on Joubert and Claasen (2006), the heuristic algorithm is used as a problem-solving approach to obtain a feasible initial solution. It can reduce the computation time for finding a solution. In this study, the initial solution was built using the Sequential Insertion heuristic method, and then the solution was repaired using the LS operators described earlier. Solomon (1987) conducted a study by comparing several heuristic methods, concluding that the sequential insertion method provides a better output value than the other methods.

Based on Campbell and Saverbergh (2002), the basic principle of the insertion algorithm is to try to insert customers between all the arcs on the current route. The sequential insertion algorithm begins by selecting a customer point as the first customer in a route after the depot point. The first customer is called the "seed." The selection of the first customer that researchers most use is the customer with the earliest time window deadline or the customer who has the farthest distance from the depot. After the initial customer is identified and entered, the SIH algorithm considers the points not included in the route while still checking the eligibility in the route.

The sequential insertion algorithm consists of a number of work procedures to find the solution. Based on the SI algorithm used for the EVRPTW problem by Keskin and Çatay (2016), a new development is made of certain processing steps that are adapted to multi-trip conditions by recharging during breaks. Customers who will be inserted on a route will be checked for eligibility first. The eligibility in question includes the eligibility of the capacity load, the fulfilment of backhaul rules, the fulfilment of the customer's time window, and the energy charge of the battery.

The rules for determining seeds apply to all initial customer formation in each trip. After updating the information, then calculate all insertion costs that have the eligibility time window and capacity. Insertion costs are obtained from adding the distance d if insertion of customer d is carried out between customer i and customer k which can be calculated as $d_{ji} + d_{ik} - d_{jk}$. The best insertion to be included in the route is the one with the minimum additional distance. Table 2 is the sequential insertion pseudocode used for initial solution development.

Table 2. Sequential insertion heuristic pseudocode

```
Algorithm 1   Initial Solution construction
Start a new route with the customer who have the earliest time window deadline
repeat
Calculate insertion cost of all unserved customers to the current route
If no customer can be added because of violating the capacity of the vehicle then
Start a new trip with the unserved customer who have the earliest time window deadline
else
Select the customer which increases the distance least and make the insertion
end if
If no customer can be added because of violating the time window then
Start a new route with the unserved customer who have the earliest time window deadline
else
Select the customer which increases the distance least and make the insertion
end if
If vehicle traverse lunch time then
Insert charging
end if
Select the customer which increases the distance least and make the insertion
end if
until all customer are served
```

Experiments and Results

All numerical experiments were performed using a single-core Intel(R) Core(TM) i5-10500H CP machine with 2.50 GHz and 8.00 GB RAM, each running Windows 11 Home Single Language. All Local Search operators were solved using the Python 3.10 programming language, and programs are solved using PyCharm. Each run of the solution approach was carried out 10 times, and the best results were presented in the next section. The total time limit allowed for the proposed algorithm was set to 300 seconds, and the time limit allowed to complete QP and CP was set to 5 seconds.

We tested the proposed solution approach on 24 tests in attitudes derived from historical data of parcel delivery companies in Indonesia. The fleet consists of an unlimited number of identical electric vehicles with a battery capacity of 38.7kWh or a maximum range of 160 km and a cargo capacity of 750 kg for Linehaul customers and 300 for backhaul customers. The vehicle is always fully recharged with a fixed recharging time. Note that more advanced functions can be used to model the behaviour of the charging process (interested readers refer to Montoya et al. (2017) for more details on nonlinear charging functions). Travel times are given in minutes and are based on the actual road network of the focus area. Customer demand is determined by the percentage of delivery and collection, which determines the percentage of customer requests that require delivery or collection, namely 30% and 70%, respectively. The number of customers varies between 10,25,50,75,100 to 300 customers (2 in each instance) based on the recharge power (G). The recharging process relies on slow charging as it takes place at the depot, hence low-power home charging is implemented. Electricity companies in Indonesia have reported that home charging typically requires between 3 kW and 6 kW of power. Our research indicates that it takes approximately 6 hours to fully charge a vehicle from 0% to 100% using slow charging, as per data provided by car manufacturers.

Table 3 above presents an example column consisting of column “C”, namely customers, and column “S”, which states the charging power used, which is 3 kW and 6 kW for each number of customers. The Initial solution column is the initial feasible solution used to build routes using Sequential Insertion. Initial Solution column consists of column “Kv”, which states the number of vehicles used, and the “Sol”. column, which is a solution resulting from the development of the Initial solution. The number of vehicles used in the initial solution increases with the number of customers. Interestingly, vehicles that recharge with a 3 kW power source require more units compared to those that recharge with a 6 kW power source, even when the number of customers is the same. For example, if there are, If the vehicles are being charged at 3 kW power, it would require 10 vehicles to complete the charging process. However, it would take 10 vehicles to complete the charging process when recharging with 3 kW power. However, if the charging power is increased to 6 kW, only 7 vehicles would be required. This is due to the fact that the amount of energy put into the battery depends on the charging power used. If electric vehicle batteries take too long to recharge, it can cause service delays and violate time windows for customers, which is especially crucial for parcel delivery. Similarly, the initial solution for the Sol. column indicates the completion value of the solution in terms of distance (kilometers). As more customers and vehicles are utilized, the distance increases. This is because more vehicles enable additional trips, resulting in an increase in the distance traveled to return and depart from the depot.

Table 3. Comparison among different Local Search operators

1	2			3	4		5		6		7		8	
Instance	Initial Solution			BS	Shift (1,0)		Swap (1,1)		Swap (2,2)		Relocation		Reinsert	
C	S	v	Sol.		Sol.	Gap	Sol.	Gap	Sol.	Gap	Sol.	Gap	Sol.	Gap
10	3	1	51.45	40.23	42.24	41.28	40.28	0.05	41.77	1.54	47.04	6.8	40.23	0
10	6	1	51.45	32.19	45.5	13.31	41.19	9	32.19	0	40.69	8.5	41.56	9.37
25	3	1	116.31	95.63	111.35	15.72	102.57	6.94	95.63	0	109.28	13.65	106.89	11.26
25	6	1	116.31	99.71	114.58	14.87	109.61	9.9	99.71	0	110.49	10.78	103.33	3.62
50	3	2	180.55	164.76	174.76	10	166.59	1.83	167.92	3.17	170.28	5.52	164.76	0
50	6	2	180.55	160.11	172.99	12.89	165.55	5.44	160.11	0	173.45	13.34	171.27	11.16
75	3	3	242.34	221.87	239.34	17.47	231.06	9.19	221.87	0	230.89	9.01	231.73	9.86
75	6	3	304.13	286.15	301.28	15.13	295.99	9.83	295.06	8.9	295.59	9.43	286.15	0
100	3	5	592.74	576.64	585.13	8.49	577.09	0.45	583.87	7.23	589.29	12.65	576.64	0
100	6	4	585.54	572.36	579.57	7.21	572.36	0	572.88	0.53	578.91	6.55	574.17	1.81
125	3	5	646.35	629.04	640.22	11.18	640.9	11.86	635.25	6.21	637.47	8.44	629.04	0
125	6	4	633.53	622.28	630.82	8.54	624.13	1.85	622.28	0	624.54	2.26	624.37	2.09
150	3	6	770.63	755.08	766.63	11.55	756.45	0	755.08	0	758.28	3.2	759.19	4.11
150	6	5	754.05	738.05	752.96	14.91	741.02	2.97	738.05	0	746.2	8.15	743.86	5.81
175	3	7	921.21	906.44	915.29	8.85	906.51	0.07	912.55	6.11	915.97	9.52	906.44	0
175	6	6	897.38	877.53	896.19	18.66	889.58	12.05	877.53	0	891.94	14.42	886.31	8.78
200	3	9	1062.32	1048.07	1056.26	8.19	1048.07	0	1048.58	0.52	1051.62	3.56	1053.1	5.04
200	6	7	1026.63	1008.9	1017.62	8.72	1022.35	13.45	1010.43	1.53	1021.15	12.26	1008.9	0
225	3	9	1154.33	1138.08	1148.06	9.97	1149.44	11.36	1138.08	0	1146.07	7.99	1140.33	2.25
225	6	7	1129.64	1115.64	1127.75	12.12	1120.28	4.65	1115.64	0	1119.52	3.88	1122.43	6.79
250	3	10	1386.99	1371.61	1382.35	10.74	1371.61	0	1374.26	2.65	1378.5	6.9	1375.32	3.72
250	6	8	1356.09	1344.43	1350.3	5.87	1344.43	0	1345.4	0.97	1345.59	1.16	1349.68	5.25
300	3	11	1551.08	1534.91	1546.27	11.35	1542.46	7.54	1537.35	2.44	1544.36	9.45	1534.91	0
300	6	8	1519.53	1507.7	1513.09	5.4	1508.39	0.69	1509.12	1.42	1511.78	4.08	1507.7	0
Average			717.96		712.94	12.6	707	4.96	703.78	1.8	709.95	7.98	705.76	3.79

Table 4. Run time of different Local Search operators

Instance			Run time				
C	S	Kv	Shift (1,0)	Swap (1,1)	Swap (2,2)	Relocation	Reinsert
10	3	1	10.4	39.75	28.18	26.67	35.88
10	6	1	21.06	31.08	40.33	52.9	18.53
25	3	1	45.35	47.02	70.33	82.49	80.34
25	6	1	45.59	22.3	39.64	37.35	45.1
50	3	2	50.33	36.1	53.64	30.08	29.09
50	6	2	36.99	60.66	56.36	40.01	49.78
75	3	3	159.09	145.34	164.22	162	147.76
75	6	3	190.12	171.44	186.38	189.18	171.49
100	3	5	288.16	319.77	307.303	305.19	305.43
100	6	4	309.06	153.83	176.51	190.18	182.69
125	3	5	592.46	417.33	464.8941	418.66	436.33
125	6	4	368.83	215.72	252.277	215.03	407.8
150	3	6	568.47	411.33	252.277	402.53	431.15
150	6	5	381.14	206.12	449.9006	201.93	426.37
175	3	7	642.64	485.42	564.028	470.6	606.39
175	6	6	528.5	352.4	440.4486	357.02	578.53
200	3	9	535.43	363.42	449.4251	362	732.62
200	6	7	415.44	263.95	339.6964	259.24	692.34
225	3	9	610.47	423.22	516.843	433.82	730.27
225	6	7	496.89	316.66	406.78	327.84	708.65
250	3	10	705.23	533.38	619.3081	535.31	970.73
250	6	8	510.08	350.96	430.5204	347.74	925.64
300	3	11	933.18	741.24	837.209	752.13	1126.69
300	6	8	741.37	588.52	664.9457	588.08	1093.34

The results of each operator can be found in columns 4 through 8, with column 3 designated as "BS," indicating the best result attained by any of the operators in each instance. Each operator is represented by two columns: "Sol" and "Gap." The "Sol" column displays the result produced by each operator in each instance, while the "Gap" column reveals the disparity between the "Sol" result and the value in the "BS" column. The average gap obtained can be seen in Table 5. Table 4 showcases the average duration spent looking for a solution in the run timetable. It is important to note that generating a solution takes longer when the instance size increases. For example, as seen in Table 2, it takes more time to generate a solution for 300 than 200 customers. Furthermore, the inter-route operator, which involves using the order Swap (2,2) - Swap (1,1) - Shift (1,0), takes longer than the intra-route operator that uses the Relocation-Reinsert order. Transferring neighbours between routes requires more complex combinatorial work than intra-route transfers.

Table 5 Comparison of average solutions

Component	Average Sol.	Average Gap
Initial Solution	717.96	15.99
Shift (1,0)	712.94	12.60
Swap (1,1)	707.00	4.96
Swap (2,2)	703.78	1.80
Relocation	709.95	7.98
Reinsert	705.76	3.79

Table 5 compares the results of various LS operators and shows that all of them outperformed the initial solution. This suggests that the resulting operator can enhance the obtained solution. The Swap (2,2) operator generated the most optimal solution, as indicated by the average gap in Table 5. This operator explores a larger solution space as the processing time increases. Reinsert follows Swap (2,2) and performs well because it systematically explores each node of the created environment. Swap (1,1) demonstrates a smaller gap than Reinsert and offers a better solution than Relocation, as it exchanges one node's space with another on a different route, rather than on the same route. Shift (1,0) produces a lower solution compared to other operators since moving a customer node to another route can potentially disrupt the vehicle capacity. To summarize, from the above extensive experiments, it is demonstrated that the inter-route Swap (2,2) operator is the most effective LS approach for solving MT-EVRPTW out of all five investigated LS methods.

Conclusions and Future Research

In this paper, we investigate the MT-EVRPBTW, a variation of the VRP that takes into account multiple trips, time windows, and backhaul using electric vehicles. We present a mathematical model that aims to minimize the total distance traveled. To solve the MT-EVRPBTW, we use the Sequential Insertion Heuristic to develop an initial feasible solution. We then introduce five widely used Local Search operators (LS) to further improve the solution: Inter route operators (Shift (1,0), Swap (1,1) and Swap (2,2)) and intra-route operators (Relocation and Reinsert). We compare the quality of the resulting solutions in real-world package delivery cases in Indonesia. All LS operators show good performance in generating solutions compared with the initial solution. Swap (2,2) is the most effective LS operator, followed by Reinsert and Swap (1,1), in achieving good performance in solving MT-EVRPBTW.

Based on the above investigations, we highly recommend using the above LS operator in developing new effective optimization methods for such difficult problems. Further work can be done by combining several local searches to explore the search space and obtain out of the optimum trap. Furthermore, since the MT-EVRPBTW is a new model, there is a need for extensive attention to design the addition of other VRP variants, such as heterogeneous and partial recharging schemes that consider the length of time for recharging vehicles to get closer to the real system.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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