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MULTI-VEHICLE CAPACITATED VEHICLE ROUTING PROBLEM FOR RICE COMMODITIES IN INDONESIA CONSIDERING THE FACTORS OF WEATHER-INDUCED DAMAGES AND CARBON EMISSIONS

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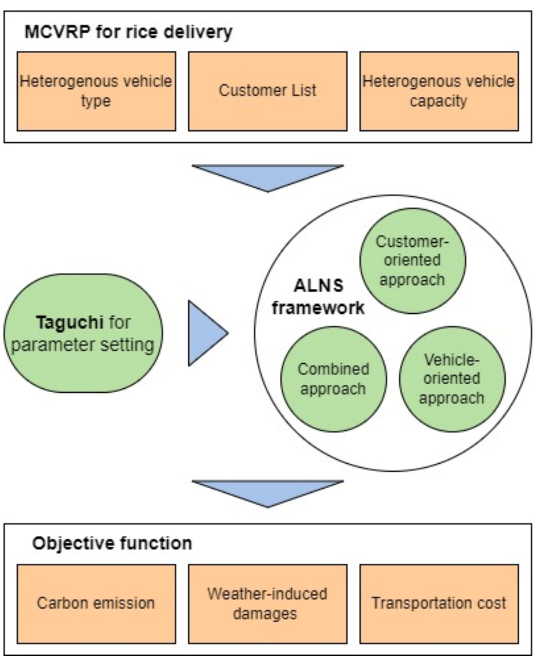
Graphical abstract



Abstract

This research discussed the Multi-Vehicle Capacitated Vehicle Routing Problem (MCVRP) in the rice commodity supply chain. This study considered the impact of weather conditions and carbon emissions on route decisions. These factors influenced travel time and rice quality, which can lead to delays, route changes, and increased supply chain costs. To account for weather conditions, the proposed model integrated historical weather data into route decisions. Additionally, the model incorporated carbon emissions as a significant factor in route decisions, aiming to reduce the environmental impact of transportation. This was achieved by considering vehicle fuel consumption and corresponding carbon emissions, optimizing route decisions to minimize the overall carbon footprint. The objective of this research was to develop a routing model that minimizes total costs while adhering to vehicle capacity constraints and customer delivery demands. Adaptive Large Neighborhood Search (ALNS) was proposed as an optimization method to solve the problem. Particularly, novel destroy and repair operators of ALNS were developed to specifically reduce the transportation cost, emission cost, and lost sales cost due to weather-induced damages. The results indicated that the proposed ALNS significantly decreased delivery expenses compared to the initial solution, achieving a 32% reduction in costs. The ALNS algorithm yielded superior outcomes compared to the standard LNS with lower objective and faster computing time. This research contributed to the development of sustainable supply chain practices in the rice commodity industry. The proposed approach provided a solution for MCVRP that considered weather conditions and carbon emissions while ensuring efficient commodity transportation.

Keywords: Rice Supply Chain, Multi-Vehicle Capacitated Vehicle Routing Problem, Carbon Emission, Weather-Induced Damages, Adaptive Large Neighborhood Search

1.0 INTRODUCTION

Agriculture plays a vital role in achieving food self-sufficiency, generating employment opportunities, and increasing income for the populace, particularly farmers [1]. Amongst the agriculture commodities, rice serves as the staple food in Asia, epecially for the majority of Indonesians. It holds cultural, nutritional, and economic importance. Indonesia is one of the world's largest rice producers, ranked after China and India, with production reaching 54.65 million tons in 2020 according to the Food and Agriculture Organization (FAO) [2]. Ensuring a consistent and reliable supply of rice to every corner of the nation is paramount for maintaining stability, preventing food shortages, and mitigating the risks associated with external supply disruptions.

The rice supply chain in Indonesia is a complex issue due to various interconnected challenges. Typically, the supply chain involves logistics processes, distribution management, storage, and processing of materials, as well as information within the flow of the supply chain [3]. These stages are intricately linked, and disruptions or inefficiencies at any point can reverberate throughout the entire chain. The geographical diversity of Indonesia, spanning remote islands and diverse terrains, further complicates the timely and cost-effective movement of rice. Additionally, factors like transportation infrastructure disparities, varying road conditions, and accessibility issues can impact the smooth progression of rice distribution from producers to consumers.

Transportation costs can exert a significant influence on domestic rice prices [4, 5] . Thus, it becomes imperative to focus on optimizing fuel efficiency and refining delivery routes as strategies to alleviate these transportation expenses. Transportation costs are a major component of the cost of rice. In some cases, transportation costs can account for up to 50% of the final market price of paddy rice [6]. The choice of transportation vehicle such as employing open or closed cargo trucks for delivery plays a discernible role in both rice quality and the associated delivery expenditures. Furthermore, unfavorable weather conditions can also result in diminished rice quality and grading [7, 8], subsequently impacting costs related to lost sales. Variables such as cargo weight, vehicle speed, and travel distance also exert a notable influence on the emissions generated during rice delivery. Consequently, the meticulous selection of appropriate delivery distances emerges as a pivotal aspect in minimizing delivery-related risks, curtailing emissions, and ultimately reducing delivery costs.

In addressing the challenges of rice distribution, the need for an optimized supply chain flow that can streamline the delivery process to consumers, including processing facilities, becomes paramount [9]. One approach taken to tackle this is to find the optimal routes for the delivery process and optimize the utilization of operational vehicles. This aims to minimize costs and air pollution in the distribution process. As such, in this study, the routing problem for rice supply chain is modelled as the multivehicle capacitated vehicle routing problem (MCVRP). Two decisions are determined in this model: selecting appropriate vehicles to transport the commodity and establishing optimal route for each vehicle.

To seek an optimal solution, this study addressed MCVRP of rice commodity using metaheuristic approaches. Metaheuristics possess the ability to obtain solutions that are close to optimal or even globally optimal [10]. Specifically, the adaptive large neighborhood search (ALNS) is chosen due to its flexibility in designing solution alteration mechanisms in the destroy and repair processes [11]. Hence, this study will also develop tailored destroy and repair mechanisms suitable for the rice commodity supply chain issue in Indonesia. The contributions of this research are:

1. This study formulates a mathematical model for the Multi-Vehicle Capacitated Vehicle Routing Problem within the rice commodity supply chain, considering weather conditions and carbon emissions. To our knowledge, there have been no studies that delve into a similar case.

2. This research introduces the adaptive large neighborhood search as an optimization method. Furthermore, it proposes novel destroy and repair mechanisms that align with the rice commodity supply chain issue in Indonesia. This mechanism primarily aims to minimize lost sales costs arising from adverse weather conditions and to minimize carbon emissions.

2.0 LITERATURE REVIEW

The vehicle routing problem (VRP) is a classic optimization problem in the field of operation research and logistics. It has been widely studied for a variety of applications, from package delivery [12, 13, 14], waste collection [15, 16, 17, 18], healthcare [19, 20, 21], and agriculture supply chain [22, 23, 24, 25], including distribution of rice commodities [26, 27].

In solving VRP, the capacity of vehicles is a critical factor to reflect real-life distribution cases. The Capacitated VRP (CVRP) is a variant of VRP that introduced the concept of vehicle capacity constraints, ensuring that the goods delivered do not exceed the capacity of the vehicles [28]. Here, all vehicles are assumed to be identical and have the same capacity. In real world applications, many companies use different types of vehicles. Bigger size vehicles are used to serve customers that require larger volumes of orders whilst smaller vehicles can be used for last-mile distribution. For such cases, the heterogeneous CVRP enables multiple vehicles with different capacities or speeds [29, 30, 31].

CVRP can be addressed through several methods, including exact methods [32, 33], heuristics [34, 35], and metaheuristics [36, 37, 38]. Whilst exact methods can perform well on small-scale problems such as discussed in [39, 40, 41], they can be computationally very expensive and may not be able to find solution for large-scale problems. Heuristic methods offer faster solutions and are preferable for larger problems [42, 43, 44]. However, these methods are not guaranteed to find an optimal solution for CVRP. Since these methods rely on expert knowledge, the quality of solution hinges on how well the hand-engineering rules are designed. On the other hand, metaheuristics often outperform exact methods and simple heuristics in solving complex problems like the CVRP. A few examples of these include the application of an ant colony optimization (ACO) to minimize the total distance travelled for vehicles in a max single depot CVRP [45]. Another study proposed a metaheuristic approach based on an iterated local search (AILS) with an objective to minimize the sum of cost in heterogeneous fleet VRP [46]. The method was first introduced to solve for multivehicle CVRP which then improved in [47] by incorporating a set partitioning (SP) formulation, creating a hybrid algorithm which outperformed the previous solutions. Building upon ILS foundation, an adaptive iterated local search (AILS) framework using an automatic diversity control mechanism was introduced to solve CVRP [48]. The problem was further extended to multivehicle CVRP [49], solving for 5 variants characterized by their fleet size (limited or not) and the cost associated with the delivery (dependent on the distance travelled or not).

In Indonesia, rice is a staple food and one of the primary commodities for the nation. Rice distribution plays a crucial role in ensuring food security and economic stability. Several studies have been conducted to address VRP for rice commodities. A mixed integer nonlinear programming model (MINLP) was used to minimize the cost for transporting food grain from procurement centers to the state warehouses by optimizing the transportation, inventory, and operations [50]. Colony algorithm (ACO) and genetic algorithm (GA) were employed to minimize the transportation and penalty costs in distribution of rice [52]. Another study on rice distribution focused on rote distribution in East Lombok Regency, Indonesia using the Differential Evolution (DE) algorithm and Large Neighborhood Search (LNS) algorithm method [51]. Another metaheuristic method was employed to minimize costs across the rice supply chain in Iran through the combination of Genetic Algorithm and Particle Swarm Optimization (PSO) [52].

With a diverse geography, the transportation network is Indonesia is exposed to a variety of weather-related challenges such as heavy rainfall, flooding, and road degradation, which can disrupt the transportation of rice commodities. The CVRP, when extended to consider weather-induced damages, can provide a framework for devising routes that account for potential disruptions, thereby enhancing the resilience of the rice commodity distribution network. Such disruptions have been previously explored in [53]. The study employed a mixed-integer non-linear approach to manage transportation disruptions by reconfiguring road networks. The proposed algorithm skipped one of several customers and found alternative storage locations for shipments that were originally scheduled to be picked up or delivered at the skipped destinations. Another study considered impacts of disruption in UAV routing problem by proposing a method of proactive-reactive planning [54]. The transportation of goods to customers initially carried by homogenous vehicles which then extended to consider multi depot CVRP [55]. There is also a growing emphasis on environmental sustainability which necessitates consideration of carbon emissions into the CVRP framework such as discussed in [56, 57, 58, 59, 60]. The transportation sector also contributes to carbon emissions which are a major cause of climate change. Integrating carbon emissions into the CVRP is a practical way to promote sustainable logistics practices in Indonesia.

In this study, we proposed multivehicle CVRP (MCVRP) to optimize the distribution of rice commodities in Indonesia by considering weather-induced damages and carbon emissions. We employed an adaptive large neighborhood search (ALNS) as an optimization method, which has been shown to outperform other algorithms in similar studies [61, 62]. We also proposed a novel destroy and repair mechanism tailored to the rice commodity supply chain issue in Indonesia. To the best of our knowledge, this is the first study to address this issue. The findings of the study can provide insights and strategies that can significantly improve the management of rice commodity distribution systems in Indonesia.

3.0 PROBLEM FORMULATION

Here, we describe the mathematical model of the MCVRP for rice delivery. The proposed model aims to minimize the total cost, which consists of transportation cost, lost sales cost, and carbon emission cost. The mathematical model being presented considers a range of factors, encompassing shipping costs relative to distance covered, carbon emission expenditures throughout the journey, and the potential costs incurred due to lost sales during rainy seasons or in cases where rain coincides with ongoing deliveries. Table 1 lists the notation of indices, sets, parameters, and variables used in the mathematical model.

Table 1 List of notations

Index and Set	
J	Set of depot and customers, $J = \{1, 2, 3, \ldots, n\}$
K	Set of vehicles, $K = \{1, 2, 3, \ldots, m\}$
i, j	Index of depot and customer, $i, j \in J$
k	Index of vehicle, $k \in K$
Parameter	
C_k	Capacity of vehicle $k = 1,2, \ldots, m$
Q_j	Demand of customer $j = 1,2, \ldots, n$
e_{rc}^k	Carbon emission rate cost of vehicle k
d_{ij}	Distance between node i to node j
c_{ij}^k	Unit transportation cost per kilometer of vehicle k
P_{LSC}	Lost sales cost per kilogram
$\theta_k \begin{cases} 1 \text{ if } k \in K_o \\ 0 \text{ if } k \in K_c \end{cases}$	Parameter which has value of 1 if vehicle k has open box $k \in K_o$, 0 otherwise
Variable	
x_{ij}^k	Binary decision variable, 1 if vehicle k transports rice from node i to node j, 0 otherwise
y_i^k	Binary decision variable, 1 if customer i is served by vehicle k, 0 otherwise
w_{ij}^k	Continuous variable which represents the weight of the payload transported by vehicle k from node i to node j.

In the model there is a set of customers $j = 1,2,\ldots,n$ with demand Q_j which must be served by the depot $i = 0$. There is a set of vehicles $k = 1,2,\ldots,m$ that can be used to deliver the rice to customer j. The vehicles belong to two major categories based on the box type, enclosed box truck K_c and open box truck K_o. Each vehicle has a capacity C_k and specific characteristics, either open or enclosed box. The distance d_{ij} from depot to customers and between customers are deterministic based on the coordinate of each node. The transportation cost is influenced by the total travelled distance of each vehicle and its rental cost.

Lost sales cost refers to the expenses incurred due to a decrease in the quality of rice being transported to consumers. In the case of this rice shipment, the lost sales cost arises from the diminished quality of rice caused by exposure to rain during the transportation process. The cost of lost sales per kilogram P_{LSC} represents the expense linked to the quality reduction. This cost of quality reduction per kilogram amounts to Rp 200. The rice delivery using an open box truck bears risk of quality degradation since the commodity is exposed to rainfall, especially during rainy season, while the enclosed box truck is free from this risk. However, the rental cost of enclosed box trucks is higher, hence it is important to select the most efficient mode of transport.

The carbon emission cost, denoted as e_{rc}^k, is the expense incurred during transportation used for delivering goods. The total carbon emission cost is derived from the carbon generated by the vehicle used e_r and the carbon tax cost P_e. In the calculation of carbon emissions produced by the vehicle, we adopt the formulation developed by Wen et al. [63]. The formulation for carbon emission cost calculation is influenced by carbon emission parameter e_r, the distance between the starting and ending points d_i, the average vehicle speed v, individual vehicle capacity C_k, the weight of the payload transported from the starting to the ending point w_{ij}^k, and parameter α_1 and α_2. Here, we assume constant value of vehicle speed v, parameter α_1 and α_2. The complete mathematical model for MCVRP for rice delivery is presented as follows.

Objective function

$$\min F = \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=1}^{n} x_{ij}^k\, d_{ij}\, w_{ij}^k\, e_{rc}^k + \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=1}^{n} x_{ij}^k\, d_{ij}\, c_{ij}^k + \sum_{k=1}^{m}\sum_{j=1}^{n} w_{ij}^k\, P_{LSC}\theta_k y_i^k \quad (1)$$

Subject to:

$$\sum_{k=1}^{m}\sum_{i=0}^{n} w_{ij}^k \geq Q_j \qquad \forall j = 1,2,\dots,n \quad (2)$$

$$\sum_{k=1}^{m} y_i^k = m \qquad \forall i = 0 \quad (3)$$

$$\sum_{k=1}^{m} y_i^k = 1 \qquad \forall i = 1,2,\dots,n \quad (4)$$

$$\sum_{i=0}^{n} x_{ij}^k = y_i^k \qquad \forall j = 1,2,\dots,n;\ k = 1,2,\dots,m \quad (5)$$

$$\sum_{j=0}^{n} w_{ij}^k \leq C_k \qquad \forall k = 1,2,\dots,m \quad (6)$$

$$x_{ij}^k \in \{0,1\},\quad y_i^k \in \{0,1\} \qquad \forall i = 0,1,\dots n;\ j = 1,2\dots n;\ k = 1,2\dots m \quad (7)$$

The objective function (1) is to minimize total cost, which is the accumulation of transportation cost, lost sales cost, and carbon emission cost. Constraint (2) ensures that the product delivered to customer j must not exceed its demand Q_j. Constraint (3) ensures that each route starts from depot $i = 0$. Constraint (4) provides a warranty that a customer j is served by a vehicle k. Constraint (5) states that there is a route from depot to customer j if customer j is served by vehicle k. Constraint (6) is capacity constraint of the vehicles in which the product allocated to a vehicle k must fulfill the limit of its capacity C_k. Lastly, Constraint (7) limits the value of decision variables as binary variables.

Algorithm 1: Proposed ALNS for MCVRP for rice commodity

```
input: an instance (J, T, τ, φ),
       ALNS parameters (Γ1, Γ0, α, Q1, Q0, λ, β)
initialize feasible solution P;
calculate σ;
set P* ← P, σ* ← σ
initialize weights ω_d^- and ω_r^+;
while stopping criterion is not reached do
  select the destroy D^- and repair R^+ using roulette wheel
  by considering the weights;
  apply (D^-, R^+) to yield P';
  calculate σ';
  ψ = exp(−(σ' − σ) / K(Γ));
  if σ' ≤ σ
    if σ' ≤ σ*
      P* ← P', σ* ← σ';
    end if
    P ← P', σ ← σ';
    q = U(0,1);
  elseif q < ψ
    P ← P', σ ← σ';
  end if
  update ω_d^- and ω_r^+;
  update Γ_{x+1} ← αΓ_x;
end while
output: P*, σ*
```

4.0 METHODOLOGY

The optimization process for MCVRP for rice supply chain is carried out using the Metaheuristic approach, specifically the Adaptive Large Neighborhood Search (ALNS) algorithm. This algorithm is an enhancement of the Large Neighborhood Search (LNS) algorithm. One of the most important benefits of ALNS is the ability to balance the intensification and diversification of searching process by adjusting its destroy and repair operators [11]. In this study the ALNS is used to determine two critical decisions: selecting vehicles and optimizing the route of selected vehicles. The objective is to minimize the total transportation cost, lost sales cost, and emission cost. The entire process of creating the ALNS algorithm can be observed in Algorithm 1.

The initial step in creating the ALNS algorithm involves initializing method parameters which are initial temperature Γ_0, final temperature Γ_1, cooling rate α, decay λ, beta β, and degree of destruction Q as well as the problem parameters which are the vehicles, distributors, demand, vehicle capacity, lost sales cost per unit, and emission cost per km. The process begins by stochastically initializing a feasible solution P. Next, the fitness evaluation is performed to calculate the total cost σ. ALNS employs two categories of operators: destroy D^- and repair R^+ operators. Each operation type has associated weights, labeled as ω_d^- and ω_r^+ which determine the likelihood of selecting each method during every iteration. During each iteration, the solution P is modified using the chosen destroy D^- and repair R^+ operators, resulting in the updated solution P'. Once again, fitness evaluation is applied to the updated solution P', and the total cost σ' is computed. The total cost σ' of the updated solution is then evaluated according to the Metropolis criterion, and the weights of each operator are adjusted. This iterative process continues until the termination condition is met which is when the current temperature Γ_c reaches the final temperature Γ_1.

4.1 Solution Representation

The solution structure for the MCVRP consists of two major parts: the customers and vehicles. In the customer part, the solution follows the permutation representation similar to those of TSP. The solution representation indicates the sequence of customer P to be visited by delivery trucks, so that it is strictly permutation while redundancy is prohibited.

Table 2 The solution representation for the MCVRP

Customer	6	4	1	2	7	9	8	3	10	5
Vehicle	1	3	2	1	1	3	3	2	2	1

Table 2 describes the solution for MCVRP. There are ten customers $j = 1,2,\ldots,n$ to be visited by a set of vehicles $k = 1,2,\ldots,m$. In this solution representation, the route for vehicle k = 1 is $j_6 \to j_2 \to j_7 \to j_{10} \to j_5$. The customers are prohibited from being visited by a truck while this truck is still in delivery process to other customers, thus prevents overtaking.

4.2 Solution Initialization

In this initial phase of solution development, the objective is to determine the outcomes of the initial objective function before proceeding with optimization using the metaheuristic method involving the ALNS algorithm.

The first step involves inputting the data that has been collected for the system development process. This data comprises the number of customers n, the distance matrix encompassing all customers and the depot d_{ij}, customer demands Q_j, vehicle capacity C_k, the number of utilized vehicles k, vehicle transportation cost per kilometer C_{ij}^k, average vehicle speed v, carbon emission parameter e_r, parameter α_1 and α_2.

The initial stage entails generating an initial solution by placing vehicles and customers. This process involves randomly assigning vehicles and customers, resulting in random pairings between customers and vehicles. The subsequent stage involves assessing the capacity of vehicles in relation to their respective demands. If the existing demand exceeds the capacity of a given vehicle, it must be replaced with a vehicle possessing more sufficient capacity. This replacement process is also contingent upon the vehicle's capacity, which must exceed the carried demand. If the vehicle's capacity still proves adequate to accommodate the demands of different customers, deliveries will be consolidated using that vehicle simultaneously.

4.3 Adaptive Mechanism

Moving on to the next stage, the selection of destroy and repair operators takes place. The selection process involves calculating the cumulative destroy weights that have been acquired. Within the ALNS framework, the choice of destroy and repair operators is carried out through an adaptive approach. This selection is achieved using a roulette wheel technique, wherein the likelihood of selecting each operator is influenced by its past performance. Each operator is assigned a weight (referred to as ω_d^- for destroy operators and ω_r^+ for repair operators) that influences the probability of a specific operator being chosen. The probability of a destroy operator d^- and a repair operator r^+ to be selected can be formulated respectively as follows.

$$P(d^-) = \omega_d^- \Big/ \sum_{d \in D^-} \omega_d^- \qquad \forall\, d \in D^- \tag{8}$$

$$P(r^+) = \omega_r^+ \Big/ \sum_{r \in R^+} \omega_r^+ \qquad \forall\, r \in R^+ \tag{9}$$

Where $P(d^-)$ is the probability of destroy operator d^- to be selected by considering its weight ω_d^- and $P(r^+)$ is the probability of repair operator r^+ to be selected by considering its weight ω_r^+. As the iterations progress, the weights undergo dynamic updates and adjustments influenced by the historical performance and the modulation of the decay parameter λ. This decay parameter, denoted as λ, governs the responsiveness or magnitude of weight modifications. With this adaptive mechanism, the operator with good historical performance in previous iteration will be assigned higher value of weight, which subsequently will have higher chance to be selected in the current iteration.

4.4 Destroy Operator

Upon selecting the destruction process, the subsequent step involves its implementation. Two distinct types of destruction operators were proposed: random destruction, which randomly selects nodes, and distance-based destruction, which is based on the farthest travelled vehicles. From these choices, one type is chosen adaptively, and the selected approach undergoes execution through one of three random auxiliary mechanisms. These mechanisms are outlined as follows:

1. Customer-oriented approach

   If the random destruction mode is opted for, this mechanism engages in the randomized removal of a predetermined number of customers. These selections are made in a stochastic manner. Alternatively, if the distance-based destruction mode is selected, this mechanism pinpoints the customer that has the longest distance from the previous node. Subsequently, these chosen customers are eliminated with a destruction intensity determined according to the degree of destruction. The values of vehicles remain in the destructed node. Table 3 illustrates an example of destroyed solution using customer-oriented approach. The destroyed customers are highlighted.

Table 3 An example of destroyed solution using customer-oriented approach

Customer	6	4		2		9	8	3		5
Vehicle	1	3	2	1	1	3	3	2	2	1

2. Vehicle-centric approach

   In the event of random destruction being chosen, this mechanism randomly eradicates a set number of vehicles. Similar to the customer-oriented approach, these eliminations are based on random selections. Conversely, if the distance-based destruction mode is favored, this mechanism identifies the vehicle that has traversed the greatest distance. The customers associated with this are then unassigned to specific vehicles.

3. Combined customer and vehicle approach

   This mechanism amalgamates the aforementioned approaches. For random destruction, both customers and vehicles are randomly chosen for removal. In cases of distance-based destruction, the reference point is the cumulative travel distance of both the customer and the vehicle. Consequently, the customer and its associated vehicle with the highest combined travel distance are eliminated.

4.5 Repair Operator

Following the completion of the destruction process, during which the acquired values are temporarily eliminated, the subsequent step involves the repair phase. Within this repair stage, the values that have been subjected to destruction are reinstated using two distinct repair approaches: directed repair and random repair. Table 3 illustrates an example of a destroyed solution using a customer-oriented approach to be repaired.

The directed repair process involves a systematic validation of truck capacities, beginning with the foremost sequence number 1. This validation procedure evaluates whether the capacity of a truck is adequate or if it exceeds its load limit when considering the inclusion of the previously eliminated customer during the vehicle's delivery. In cases where the truck's capacity is inadequate, the procedure advances to sequence number 2 and subsequent ones. Conversely, if the truck's capacity proves sufficient, the customer that was initially removed will be placed within a vehicle possessing ample truck capacity to fulfill that customer's demands.

Random repair presents notable distinctions when compared to Directed repair. In the context of Directed repair, both the repair and validation procedures are executed in a systematic sequence. In contrast, the Random repair approach conducts repairs by randomly adding vehicles and/or customers on the destroyed nodes. During random repair, there is possibility of redundant value of customer which is then violating the basic constraint of MCVRP. When such conditions occur, the algorithm keeps randomly generating customer nodes until the permutation constraint is fulfilled. The random assignment of customers to a specific vehicle may also violate the capacity constraints of this vehicle. As such, an adjustment is executed by simply assigning the related customers to other vehicles. The repair process is also categorized into three mechanisms, mirroring the ones found in the destroy process. The mechanics of these approaches are elaborated as follows:

1. Customer-oriented approach

   The repair process focusing on customers initially subjected to destruction involves a step-by-step assessment. Initially, the remaining vehicle capacity is checked against the demand of the eliminated customer. If the demand fits within a vehicle's capacity, the customer is integrated. Yet, if the vehicle can't accommodate the demand, an alternative unused vehicle is employed. If vehicle options are still inadequate, the search is directed towards the largest capacity vehicle. However, if this largest vehicle contains prior customers, they are redistributed among other vehicles.

2. Vehicle-oriented approach

   Addressing vehicles destroyed during the process, this repair method commences with validating customer demands against repaired vehicles. If demands fit, priority is given to the customers. Otherwise, alternatives are chosen. In cases where the selected vehicle does not suit all customer criteria, a replacement vehicle is sought. If a fitting alternative is elusive, the largest-capacity vehicle is chosen, with prior customers redistributed randomly.

3. Combined customer and vehicle approach

   This method encompasses both customer and vehicle restoration following destruction. Initial validation gauges unrepaired vehicle capacities against unconcluded customer demands. Once validated, repairs begin. Inadequate capacities lead to customer and demand transfers. If demand still exceeds vehicle capacity, an available, adequately capacitated vehicle substitutes. Persistent excess demand triggers selection of the largest-capacity vehicle. The displaced demand is then matched with a replacement vehicle accommodating it.

4.6 Acceptance Mechanism

The conclusion of each iteration adheres to the annealing schedule of simulated annealing (SA), which is influenced by the initial temperature Γ_0, final temperature Γ_1, and cooling rate α. The cooling rate α has a balancing effect: a lower cooling rate leads to a longer time for processing due to its deceleration of the alteration process [11]. Conversely, a higher cooling rate results in a smaller number of iterations, which could potentially lead to becoming trapped in local minima, although it significantly reduces processing time. The acceptance and rejection criteria for a new solution are guided by the Metropolis acceptance criterion detailed in Eq. (10).

$$\Psi(P') = \begin{cases} e^{-\left(\frac{\sigma' - \sigma}{K(\Gamma_C)}\right)} & \text{for } \sigma' - \sigma > 0 \\ 1 & \text{for } \sigma' - \sigma \leq 0 \end{cases} \tag{10}$$

Where $\Psi(P')$ is the probability of new solution P' to be accepted. This criterion allows a new solution, even if it exhibits worse fitness than the previous one, to be accepted in the initial iterations. This approach empowers the algorithm to explore a broader scope of the search space during the early stages of exploration. Gradually, the likelihood of accepting a less optimal solution diminishes as the system approaches a state of equilibrium.

Table 4 Customer demand

No.	City	Location	Demand (kg)
1	Jakarta	Pasar Senen	9,976
2	Jakarta	Pademangan	13,131
3	Jakarta	Cipinang	7,500
4	Jakarta	Tomang	1,016
5	Jakarta	Keranji	1,888
6	Bekasi	Mustika Jaya	1,750
7	Bekasi	Cikarang	3,556
8	Bekasi	Duren Jaya	1,875
9	Bandung	Dago	6,769
10	Bandung	Karasak	1,800
11	Bandung	Cimahi	1,875
12	Bandung	Pasirkoja	1,970
13	Gombong	Pasar Gombong	3,276
14	Gombong	Desa Kalipurwo	1,573
15	Magelang	Kota Magelang	1,350
16	Semarang	Kota Semarang	930

5.0 EXPERIMENT AND RESULT

5.1 Dataset

The experiment in this research utilizes a real-world data obtained from a rice milling facility In Indonesia. The rice milling facility serves as a site for the rice production process, where the raw material used is rice with its husk intact. The rice with husk is processed within the facility to transform it into finished rice, ready for the market.

The data used for experiments includes the number of customers served by the rice milling facility (unit), quantity of rice to be shipped (kg), rice price at the time of shipment (IDR), number and type of vehicles to be utilized (unit), and truck rental cost (IDR). Table 4 presents the customers and demand, while Table 5 presents the available vehicles and their rental cost per kilometer travelled. The lost sales cost due to quality decrease is set at Rp. 200/kg and the emission rate cost are Rp 30. Further, the distance matrix between customers and depots is presented in Table 6, in which the depot is represented as 0, while 1-16 represents the customers.

Table 5 Vehicle specifications

No	Vehicle Model	Body Type		Capacity (kg)	Rental cost /km	Availability
		Enclosed	Open			
1	Pick Up truck		v	1,000	Rp 5,454	2
2	CDD Box	v		4,000	Rp 7,936	2
3	Three-axle truck with wingbox	v		20,000	Rp 16,103	2
4	Three-axle truck		v	15,000	Rp 13,565	2
5	Fuso Box	v		8,000	Rp 10,500	2
6	CDD Long		v	6,000	Rp 7,500	2
7	Single-axle Box truck	v		2,200	Rp 5,761	2
8	Tandem axle truck		v	4,000	Rp 6,185	2

Table 6 Distance matrix

Node	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	0	531	525	533	540	521	525	516	526	110	99	489	501	507	510	165	169
1	530	0	9	9	9	147	151	143	152	513	442	54	36	32	19	414	405
2	527	11	0	22	22	143	147	139	148	509	438	51	32	21	13	410	401
3	535	7	21	0	16	151	155	147	156	517	446	58	40	36	32	418	409
4	541	9	21	15	0	158	162	154	163	524	453	65	47	43	23	425	416
5	523	149	143	151	158	0	10	9	5	505	434	108	120	126	129	294	285
6	527	153	148	156	162	10	0	16	10	509	438	112	124	130	133	308	299
7	518	144	139	147	153	12	14	0	17	500	429	103	115	121	124	299	290
8	452	154	149	156	163	5	10	13	0	435	364	113	125	131	134	285	276
9	85	512	506	514	521	502	506	498	507	0	80	470	483	489	491	106	106
10	97	444	438	446	453	434	438	429	439	80	0	402	414	420	423	184	185
11	491	55	50	58	64	108	112	104	113	474	403	0	26	32	35	375	366
12	504	37	32	40	47	120	124	116	125	486	415	28	0	14	17	387	378
13	509	31	26	37	40	126	130	122	131	491	421	33	15	0	9	393	384
14	519	26	13	33	32	135	139	131	140	501	430	35	17	8	0	402	393
15	165	416	410	418	425	296	288	302	287	105	185	375	387	393	395	0	10
16	169	414	408	416	423	287	279	293	278	105	185	373	385	391	394	10	0

5.2 Design Of Experiment

Parameter settings for the ALNS algorithm are established by making several structured changes to parameter values aimed at achieving the targeted standard quality results. The Taguchi method is employed in this research for parameter setting. The Taguchi method itself is a tool for efficient and systematic optimization, and it's a testing method developed based on statistical principles and methods [64].

The Taguchi orthogonal arrays method is used in this research with 3 parameters, 3 levels, and 9 runs as shown in Table 7. In each run, the process is replicated 10 times, ensuring the best possible results are achieved. Figure 1 presents the results of experiments setting.

Table 7 Taguchi orthogonal arrays for the parameter setting

Runs	Cooling Rate	Degree of Destruction	Decay
Taguchi 1	0.9	0.3	0.7
Taguchi 2	0.9	0.5	0.8
Taguchi 3	0.9	0.7	0.9
Taguchi 4	0.95	0.3	0.8
Taguchi 5	0.95	0.5	0.9
Taguchi 6	0.95	0.7	0.7
Taguchi 7	0.99	0.3	0.9
Taguchi 8	0.99	0.5	0.7
Taguchi 9	0.99	0.7	0.8

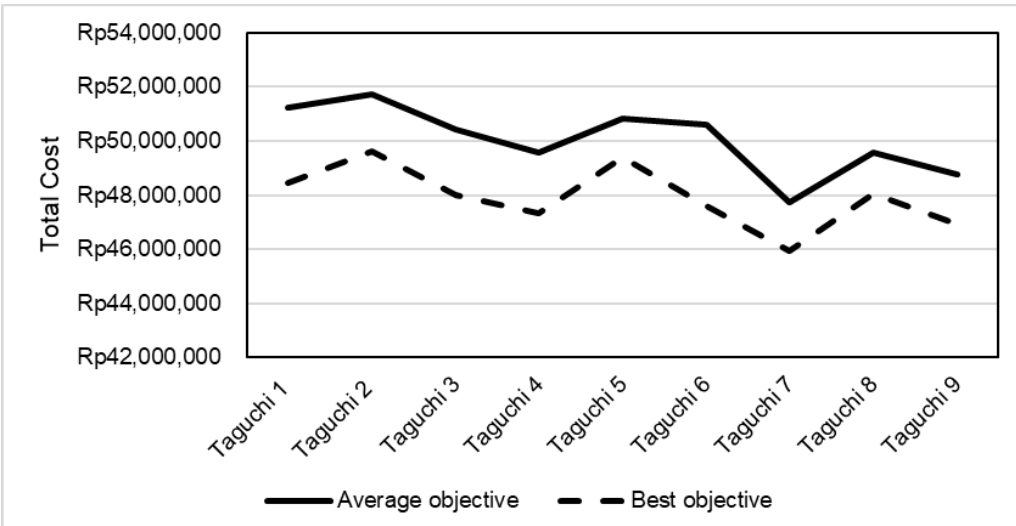


Figure 1 Results of experiment for parameter setting

The results of experiments for parameter setting indicate that Taguchi 7 run obtained the best fitness, both in terms of best and average objectives. Therefore, the parameter values of cooling rate α = 0.99, Degree of destruction $Q = 0.3$, and Decay rate λ = 0.9 are used for the numerical experiments. The rest of parameters are set as follow: initial temperature $\Gamma_0 = 1x10^6$ final temperature $\Gamma_1 = 1$, lower limit degree of destruction $Q = 0.1$, and Beta parameters β = {0.1, 0.8}. To ensure the fairness during comparison, the same parameter values are applied for both the proposed ALNS and benchmark method LNS.

5.3 Comparison Results

To evaluate the effectiveness of the proposed ALNS, numerical experiments are performed using the optimized parameter values. The comparison against the benchmark method LNS is executed in 10 replications. Figure 2 presents the comparison results between ALNS and LNS in 10 replications.

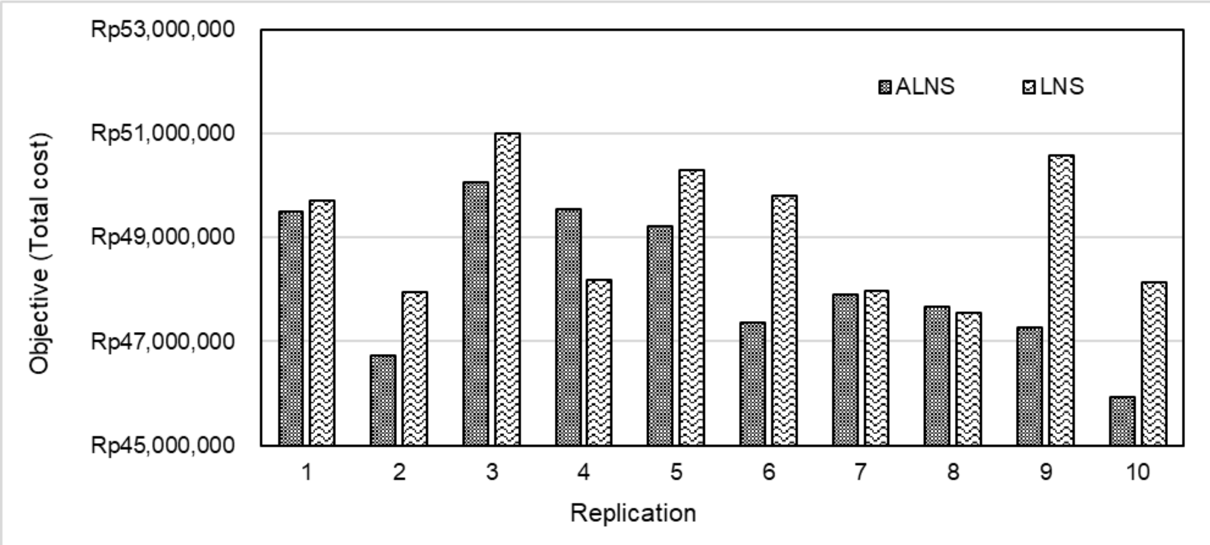


Figure 2 Comparison results between ALNS and LNS in 10 replications

The results indicate that the proposed ALNS outperformed LNS in most instances. In addition, the best and average objectives obtained by ALNS are significantly lower than the LNS. As such, it can be concluded that the adaptive mechanism of ALNS is effective in guiding the search process to prevent premature convergence and obtain near-optimal solutions. Further, the adaptive mechanism can assist the algorithm in balancing between exploration and exploitation processes in which it can adaptively adjust the selection of destroy and repair operators based on their historical performance in previous iterations.

Upon analyzing the computational times from 10 consecutive runs, the ALNS algorithm achieves a faster average time, with an average computation time of 4.98 seconds, whereas the LNS algorithm yields a longer average time of 6.48 seconds. By evaluating the obtained results, it can be concluded that utilizing the ALNS algorithm as the optimization methods for the concerned problem leads to approximately 1.50 seconds time reduction compared to the use of the LNS algorithm. Thus, it confirms the efficiency of ALNS during the search process.

Table 8 The detail results of the best obtained solution

Vehicle code	Capacity (kg)	Customer	Used capacity	Unused capacity	Travelled distance	Transportation cost	Emission cost	Lost sales cost
2	1,000	10	930	70	99	Rp 539,990	Rp 63	Rp 186,000
3	4,000	15	1,573	2,427	165	Rp 1,020,525	Rp 149	Rp 314,600
4	4,000	9	1,350	2,650	110	Rp 680,350	Rp 98	Rp 270,000
6	6,000	14,12	3,638	2,362	527	Rp 3,952,500	Rp 636	Rp 727,600
7	15,000	6,7	8,644	6,356	541	Rp 7,338,665	Rp 1,216	Rp 1,728,800
10	2,200	5	1,970	230	521	Rp 3,001,502	Rp 417	-
12	4,000	16	3,276	724	169	Rp 1,341,184	Rp 174	-
13	8,000	8	1,800	6,200	526	Rp 5,523,000	Rp 641	-
15	20,000	4,11,3	18,562	1,438	637	Rp 10,257,611	Rp 2,139	-
16	20,000	1,2,3	18,492	1,508	562	Rp 9,049,886	Rp 1,884	-

The detailed results of the experiment of the best obtained solution on the dataset is presented in Table 8. Noted that vehicles 2,3,4,6,7 are trucks without enclosed boxes. Hence, there is a possibility of quality decrease of transported rice due to weather factors, such as rain. However, this type of truck generally has lower price of rental costs, thus lower transportation costs. As such, both objectives have a partially trade-off relationship which might need further analysis.

5.4 Sensitivity Analysis

The sensitivity analysis is performed on the variation of lost sales cost per kilogram and emission cost. The experiments are executed to further test the robustness and applicability of the optimization method to solve the concerned problem under various conditions and assumptions.

5.4.1 Sensitivity Analysis Of Lost Sales Cost

For the sensitivity analysis on the effect of quality decrease due to weather, the lost sales cost per kilogram is shifted by increasing its values. Thus, there are three levels of lost sales cost per kilogram of affected rice, which are Rp. 200/kg (standard value), Rp. 400/kg, and Rp. 600/kg. The increase on this parameter represents the influence of weather on the quality decrease of rice. Noted that this phenomenon is only applied to rice commodities which are carried by open box truck. The results of the experiments with various values of lost sales cost per kilogram are depicted in Figure 3. Ten replications are executed for each level of lost sales cost.

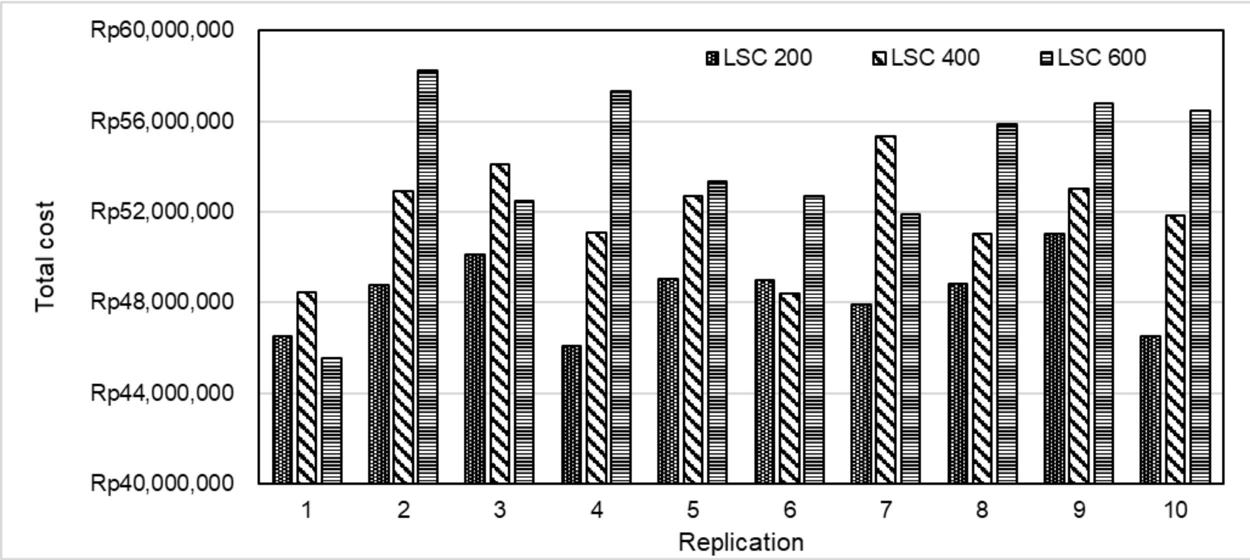


Figure 3 The total cost obtained in various levels of lost sales cost

From the sensitivity analyses conducted on the lost sales cost using costs of Rp 200/kg, Rp 400/kg, and Rp 600/kg, the average objective values obtained were Rp 48,367,821, Rp 51,882,985, and Rp 54,062,195 respectively. Based on the results, it is discernible that each average objective value experiences an incremental cost of around Rp 2,847,187 or an increase of 75% of the lost sales cost component between each level. Consequently, it can be deduced that the increase in lost sales cost would have a substantial impact on the cost, potentially leading to reduced profitability. Another significant impact of rice quality decrease due to bad weather is that it will take longer time for drying the rice until it is ready to be marketed.

5.4.2 Sensitivity Analysis Of Emission Cost

In the second scenario, the sensitivity analysis is performed to give insight on the increase of carbon emission cost. In most developing countries, including in Indonesia, the policy on carbon emission tax has not been applied and is still in feasibility studies. Here, we explore the possibility of two levels of carbon emission rate cost: Rp. 30 [65] and Rp. 471.91 [63]. Similar to the previous experiment, 10 replications are executed. Figure 4 presents the results of sensitivity analysis on various emission cost.

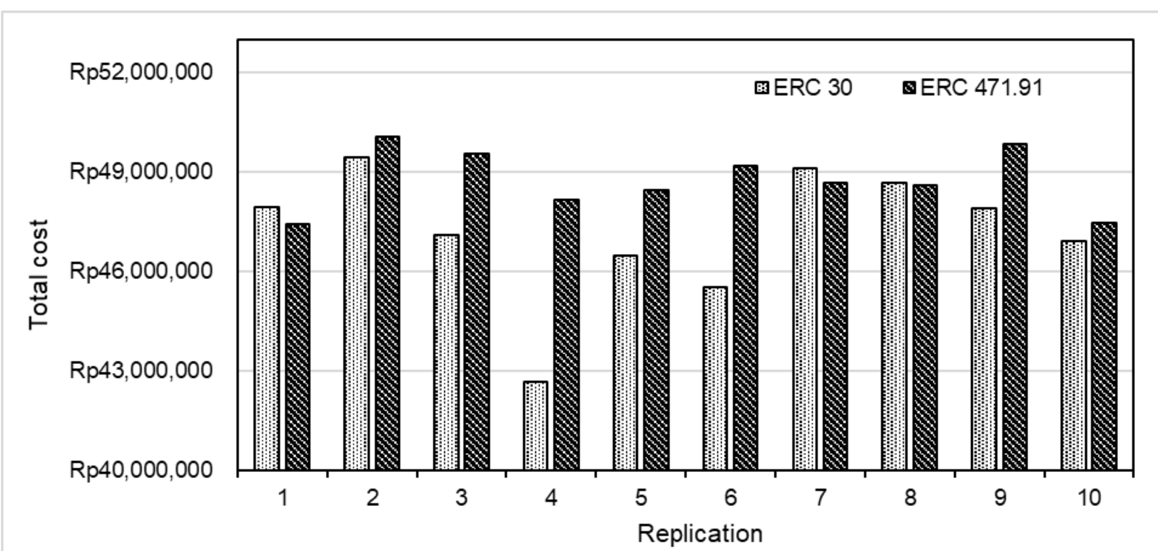


Figure 4 The total cost obtained in various levels of emission rate cost

From the two emission cost levels applied in the sensitivity analysis, the results indicate that the improvements achieved are not notably significant concerning exhaust gas emission costs. The average objective resulting from a Rp 30 emission cost amount to Rp 47,178,496, while for emission cost of Rp 471.91, the result stands at Rp 48,754,276 on average. Despite the 1473% cost increase in carbon emission cost, the net effect on the objective amounts to just Rp 1,575,780 or approximately 3% of the total cost. Consequently, it can be inferred that a substantial cost rise in exhaust gas emissions does not exert considerable influence on the eventual objective result. Albeit the emission cost contributes a small fraction of total cost, considering the emission of rice transportation is important due to huge volumes of rice transportation in Indonesia and its effects on the environment. Moreover, in the future, the carbon tax is likely increased due to growing concern of climate change.

Summarizing the two sensitivity analyses, it's apparent that increase on lost sales cost due to rice quality decrease has a more pronounced impact on the total costs compared to the effect of emission cost increase. The lost sales cost factor yields an effect where a 75% average increase between lost sales cost level can impact the total cost by around 6%, whereas the emission cost, despite a 1473% increase, influences the total cost by only 3%.

6.0 CONCLUSION

This study addresses the Multi Vehicle Capacitated Vehicle Routing Problem (MCVRP) for rice commodity delivery in Indonesia. A mathematical model has been devised to optimize delivery costs, and the implementation of the Adaptive Large Neighborhood Search (ALNS) algorithm, along with the utilization of the Taguchi method to determine optimal parameters, has successfully enhanced delivery cost efficiency. Research findings demonstrate that delivery costs can be substantially reduced compared to the initial conditions, achieving a remarkable 32% cost reduction. The selection of truck types, both open-bed and closed-bed, has been proven to significantly impact delivery costs. Unpredictable weather fluctuations can trigger unforeseen expenditures. Although the impact of carbon emissions on costs may not be substantial, in the long run, sustainable delivery practices can accumulate cost-saving effects.

Within the context of algorithm performance comparison, this study contrasts ALNS and LNS for optimizing rice delivery costs. Experimental results indicate that the employment of the ALNS algorithm yields superior outcomes compared to the LNS algorithm. While a 2% difference might seem marginal, its significance increases when ALNS is consistently applied over time. In its entirety, this research provides valuable contributions by amalgamating mathematical modelling, the ALNS algorithm, and the Taguchi method to optimize the delivery process. Consequently, supply chain costs can be effectively curbed, yielding positive ramifications for rice delivery operations in Indonesia.

Future research may focus on formulating multi-objective problems for MCVRP of rice commodity since there might be trade-offs or conflicting objectives among these cost components. As such, developing for balancing the objective of minimizing transportation cost, maintaining the quality, and reducing environmental impacts. Further, other indicators of quality and environmental impacts on rice transportation such as energy consumption, grain integrity upon arrival, emission of air pollutants, and waste generation, can be explored for future studies on solving the multi-objective transportation problem on rice commodity.

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