Spektrum Industri
Vol. 23, No. 1, 2025, pp. 71-85
ISSN 1693-6590
http://journal3.uad.ac.id/index.php/spektrum

Optimizing Container Repositioning Using a Sequential Insertion Algorithm for Pickup-Delivery Routing in Export-Import Operations

Ary Arvianto *, Dihan Chofifah Cahyani, Dhimas Wachid Nur Saputra

Industrial Engineering Department, Diponegoro University, Semarang, 50275, Indonesia
* Corresponding Author: aryarvi@gmail.com

ARTICLE INFO

Article history
Received March 17, 2025
Revised April 25, 2025
Accepted April 30, 2025

Keywords
Supply chain;
Distribution;
Sequential insertion;
Vehicle routing problem;
Container repositioning

ABSTRACT

The increasing number of empty containers significantly causes to traffic congestion and rising operational costs, thereby necessitating the development of an optimized routing model to enhance fleet utilization and minimize transportation expenses. This study focuses on optimizing container repositioning for pick-up and delivery operations using a heuristic approach derived from the Vehicle Routing Problem with Pick-Up and Delivery and Time Windows (VRPPD-TW). The proposed model employs a sequential insertion algorithm grounded in a mathematical framework and implemented in Python. Its accuracy is validated through manual calculations that correspond with the algorithmic steps. The objective is to minimize vehicle usage within the defined time constraints. This empirical study involves six nodes: a garage, two depots, two external container depots, and a port terminal, which handle the daily relocation of 44 containers for export-import activities. The model successfully reduces the number of trips from 37 to 6, demonstrating substantial optimization. The results show that the sequential insertion algorithm effectively solves the VRPPD-TW by enhancing solution space exploration, balancing workloads, and adapting to dynamic constraints. Managerial implications include a 75% reduction in fleet requirements and increased logistical efficiency. This research contributes a practical approach with the potential to lower operational costs and mitigate congestion by improving fleet utilization. However, the model has notable limitations, such as the exclusion of dynamic truck queuing times at each node and unresolved issues related to computational scalability.

1. Introduction

Globalization has significantly transformed the structure of global industry and economy. This transformation encompasses the implementation, operation, and distribution of resources on a global scale. As a result, global trade and transportation networks have also been developing rapidly (Bawono et al., 2019). Therefore, logistics plays a crucial role in managing the supply chain of companies (Hasibuan et al., 2021). Logistics management is necessary for companies to plan, execute, and control the smooth distribution of goods, services, and information (Febriyanti et al., 2022; Kusumastuti & Sugiama, 2017). One of the keys focuses of logistics is the optimization of routes and distribution of goods from the initial point to the final consumer to meet consumer demand (Saragih & Turnip, 2024).

The routing problem is known as the Vehicle Routing Problem (VRP) and has become a fundamental concept in transportation solutions (Toth & Vigo, 2015) such as, heterogeneous VRP (Arvianto et al., 2015; Joubert & Claasen, 2006), and Large-Scale Single Vehicle Dial a Ride Problem with Time Windows (Desrosiers et al., 1986).

Routing problems in export-import terminals for vehicle parts and products requires the efficient transportation of goods between inland terminals and seaports. These problems are particularly challenging due to the need to manage simultaneous pickups and deliveries of containers, ensuring timely and cost-effective operations. For instance, in inland shipping, export and import containers need to be transported between inland terminals and seaports, posing a variant of the split vehicle routing problem with simultaneous deliveries and pickups. Effective solutions to these problems can significantly reduce transportation costs and improve the overall efficiency of logistics operations (Fazi et al., 2020). The current situation will impact the quality of service provided by the container terminal (Widyawati et al., 2020).

Container routing models are critical in optimizing the transportation of containers in liner shipping networks. These models aim to minimize costs and reduce transit times by optimizing the routes and allocation of containers. Hybrid-link-based models (Wang, 2014), have combined origin-link-based and destination-link-based models to provide a more comprehensive approach to container routing. Meanwhile, tighter MIP models (Alfandari et al., 2019), used node-based modeling to improve the efficiency of barge container shipping. These models are designed to address a various constraints and objectives, including efficiency, cost reduction, and flexibility. They are essential in ensuring the smooth operation of container logistics and improving the overall competitiveness of shipping companies.

The optimization of routing and allocation in a container transport network is a significant challenge in port development. A variational inequality model has been introduced to address port congestion, considering the complexity of ship routing and allocation schemes (Meng et al., 2023). The model aims to minimize the number of vessels required and reduce transit times, while ensuring that all pick-up and delivery operations are completed within the specified time windows. This study highlights the importance of addressing container logistics issues as they directly impact the allocation scheme and vessel congestion at ports. The model provides a valuable contribution to the field of logistics and operations research, highlighting the need for efficient and effective container routing models to improve the overall efficiency of container logistics.

In the current situation, issues related to the delivery and receipt of goods at a container terminal also occur at an automotive company. The company is involved in the production of body parts for vehicles (jigs and dies), the production of vehicle components (as an exporter of vehicles and vehicle components), and the importation of vehicle components needed for vehicle assembly (as an importer).

Previous research has extensively explored various VRP associated with containers, an innovative mathematical model and large neighborhood search (LNS) algorithm have been developed to optimize container drayage operations, considering vehicle capacities, time windows, and driver regulations (Zhang et al., 2020). The LNS algorithm improves solution quality and computational efficiency by effectively navigating complex solution spaces. This approach demonstrates significant improvements in operational efficiency and cost-effectiveness in container drayage logistics. Furthermore, the Capacitated Vehicle Routing Problem (CVRP) has been developed by integrating alternative delivery and pick-up locations along with time windows (Sitek et al., 2021). A novel hybrid approach, combining metaheuristic and exact methods, is proposed to optimize this extended CVRP model. Computational experiments show that this approach significantly improves solution quality and efficiency. The study highlights the practical applicability of the modified CVRP model in real-world logistics, providing substantial cost and time savings. A variant of the split vehicle routing problem (SVRP) has been proposed to optimize barge transport between dry ports and seaport terminals, addressing simultaneous deliveries and pickups under time constraints (Fazi et al., 2020).

Utilizing a hybrid local search meta-heuristic algorithm combined with a branch-and-cut solver, the model aims to maximize barge utilization and minimize travel distance.

Advanced algorithms have been developed to optimize vehicle routing in container pick-up and delivery operations. These methodologies are designed to address the intricacies of logistical processes, emphasizing cost efficiency and the enhancement of service level (Vidovic et al., 2011). By integrating key constraints such as vehicle capacities and time windows, the proposed solutions significantly enhance the efficiency and effectiveness of container logistics operations. Moreover, an improved simulated annealing algorithm has been studied and optimized to address the vehicle routing problem with soft time windows in pick-up and delivery operations. This work emphasizes enhancing the algorithm's efficiency in managing time window constraints while ensuring optimal vehicle routing and scheduling (Deng et al., 2009). The proposed improvements demonstrate significant advancements in optimizing route planning, leading to reduced operational costs and improved service quality in logistics operations.

Various alternative methods have been proposed to address the VRP. Among these, the Nearest Neighbor and Clarke & Wright Savings approaches have been employed to optimize the distribution problem effectively (Kurniawan et al., 2014; Lai et al., 2013). Subsequently, the development of heuristic methods with tabu search was used to solve the pickup delivery with time windows problem (Lau & Liang, 2002). Heuristic methods, including the sweep algorithm (Armbrust et al., 2022; Euchi & Sadok, 2021; Nono et al., 2020) and the nearest neighbor approach (Prasetyo & Tamyiz, 2017; Suryani et al., 2018). Wulandari (2020), have evolved significantly and remain widely applied in contemporary research.

Despite significant advancements in container logistics optimization, previous research has primarily focused on either empty container repositioning or vehicle routing in isolation, often under idealized conditions that fail to account for real-world disruptions such as port closures or unexpected delays. Existing models frequently overlook the complexities introduced by time windows, split deliveries, and multiple trips, limiting their applicability to practical logistics networks. This research bridges the gap by integrating both empty container repositioning and vehicle routing within a unified framework that considers realistic constraints.

The optimization of container repositioning in export-import logistics has been extensively studied through various heuristic and exact methods, including Large Neighborhood Search (LNS), mixed-integer programming (MIP), Clarke-and-Wright, Tabu Search, and metaheuristics. However, existing models often struggle with scalability and computational efficiency when addressing real-time constraints in complex logistics networks. This study addresses these gaps by implementing a Sequential Insertion Algorithm (SIA) tailored for Vehicle Routing Problems with Pick-Up and Delivery and Time Windows (VRPPD-TW). SIA incrementally constructs optimized solutions, enhancing adaptability to dynamic constraints such as sudden changes in container availability or routing conditions. Through a mathematical model and the development of a Sequential Insertion Algorithm, the proposed solution optimizes fleet efficiency while minimizing non-value-added costs. This approach represents a significant departure from conventional studies, offering a robust and adaptable method suitable for dynamic, high-demand industries such as automotive logistics.

Logistic company in Indonesia faces significant challenges in managing its export-import operations, particularly in the transportation of containers. The imbalanced flow of goods between exports and imports leads to an increase in the number of empty vehicles and non-value-added costs. This presents a complex challenge that requires routing modeling to minimize the movement of empty trucks and improve the overall route efficiency. The developed routing model is also expected to be applicable to other similar logistics networks.

This study aimed to develop a mathematical model to solve the Vehicle Routing Problem Pick-Up and Delivery with Time Windows (VRPPD-TW) that considers time constraints for truck entry and exit. The mathematical model is subsequently translated into a Sequential Insertion Algorithm. This algorithm aims to minimize empty trailer trucks and reduce non-value-added costs, ensuring that resources are utilized efficiently, and waste is minimized. This model develops a VRPPD framework for the container sector, considering the container repositioning process. It provides a valuable solution to VRP challenges in managing export-import operations with similar characteristics. In addition, this study contributes to the development of more efficient logistics operations and reduce costs for similar companies in the industry. The research also aims to improve the overall performance of logistics operations, ensuring timely delivery and pickup of containers, and enhancing customer satisfaction.

2. Method

Based on previous research on the vehicle routing problem (VRP) for truck trailer management in container relocation (Zhang et al., 2020), the present study develops an enhanced VRP model. In this formulation, route planning is refined to permit truck trailers to perform both pickups and deliveries at the same location, and vehicles are allowed to revisit nodes if additional transportation demand exists. The model's objective function is designed to minimize the number of vehicles required to satisfy container repositioning needs. Conceptually, the model is characterized by five key variants: (a) a homogeneous fleet, wherein vehicles possess similar attributes in terms of truck type and capacity. In practice, this type of grouping is because the repositioning process only uses one type of container fleet (truck); (b) multiple trips, enabling a vehicle to serve more than one node or route within a single delivery cycle. The company does not specifically regulate the minimum number of fleet visits to container facility (nodes). Empirical data shows that each fleet may visit more than one node. Therefore, the multiple trips characteristic can be assigned in this study; (c) time windows, which enforce fixed service periods during which nodes may operate. Although operating for 24 hours, there are time restrictions (time windows) in the container yard for access in and out of the container fleet. Time window characteristics must be included in this study model; (d) split delivery, a node can be visited by more than one vehicle to fulfill the demand. This characteristic aligns with the operational constraint that container repositioning occurs at a predefined set of facility nodes, six in this study. Consequently, demand at each node, whether related to pick up or container delivery, can be satisfied by multiple vehicles independently within the designated operating hours, ensuring flexibility in resource allocation and optimizing logistical efficiency; and (e) a single product, where only one type of product (one container size) is involved in the shipping process. These characteristics become a reference for the development of the algorithm built on this model.

The solution to the VRP problem, incorporating the five specified characteristics, is approached in three primary stages: First, a comprehensive mathematical model is formulated to incorporate all the relevant characteristics, ensuring that the unique constraints and parameters are accurately captured. Second, an algorithm based on the sequential insertion technique is developed to solve the resulting optimization problem effectively. Third, this phase involves testing the optimization model using the sequential insertion algorithm. The process evaluates whether the resulting route selections comply with constraint functions and align with manual calculations. Validation is conducted by comparing the total number of tours obtained through manual computation in Excel with those generated by the algorithm-based program. Consistency between results indicates the algorithm's validity.

The VRPPD-TW solution model was developed using Python programming language on the Google Colab web-based platform. The libraries used include Streamlit for creating an interactive web application and OR-Tools for solving optimization problems in vehicle routing. After the algorithm is developed, the next step is the testing process using empirical data. The data for testing was collected directly from the field through observations and interviews with operational staff of the company. Data was gathered regarding shipment and return node data, vehicle types and quantities, operating hours, and vehicle routes. The collected data was then verified for consistency and validated by cross-checking it with historical records maintained by the company to ensure its accuracy and relevance.

The container repositioning routing process commences by determining the visitation sequence that minimizes the overall tour completion time. Notably, a single tour may consist of multiple routes, contingent upon the planning horizon. The sequence is established through a sequential insertion algorithm, whereby all potential unserved nodes are inserted iteratively. This procedure also incorporates time window constraints at pick-up and delivery nodes; if a vehicle's arrival time falls outside the designated time window, the node is excluded based on feasibility checks. The total tour completion time is then determined by summing both the travel time and the service time (including container lift-on and lift-off operations). This phase of the algorithm concludes when the demand at all nodes has been fully met. Depending on the number of pick-up and delivery nodes and the demand at each point, the process may require multiple iterations. Fig. 3 provides a detailed illustration of the completion stages in the proposed vehicle routing problem (VRP) model.

Further clarification regarding the implementation of the Vehicle Routing Problem with Pickup and Delivery and Time Windows (VRPD-TW) framework in this study is provided by decomposing the container repositioning task into four distinct categories, as depicted in Fig. 1. The first, outbound full container delivery, involves transporting fully loaded containers from the company's container yard (CY) to the port terminal. The second task, inbound full container delivery, encompasses the movement of imported containers from the port terminal to the company's CY, as well as the reverse operation. The third operation, outbound empty container delivery, entails transferring empty containers, typically those previously used for imports. Lastly, inbound empty container delivery focuses on returning empty containers.

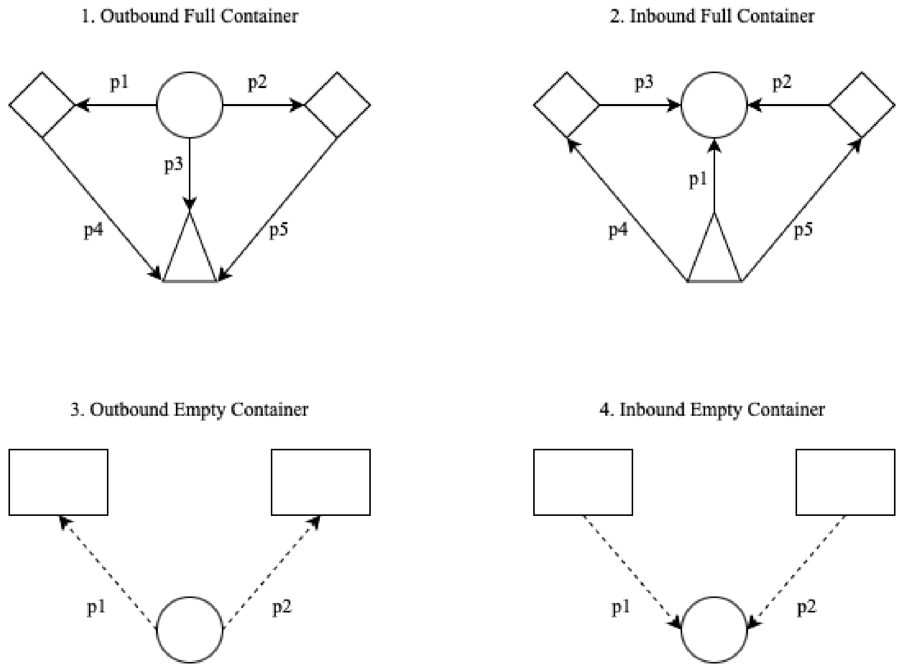

Fig. 1. Container Repositioning Task

Fig. 2. illustrates the container delivery route requirements for the company, highlighting six essential locations that container delivery trucks must visit. As an illustration of the process, the truck garage serves as the departure and return depot, while the route also includes two additional depots, two external container storage areas, and one port terminal. The company needs to relocate containers every day for the import-export process using one type of truck owned by a third-party logistics partner. The trucks operate during certain working hours every day to pick up and deliver containers.

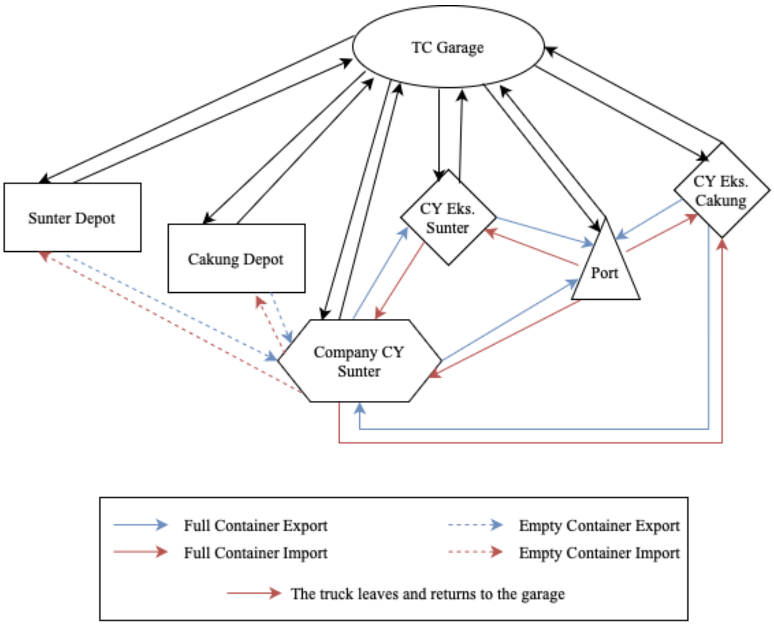

Fig. 2. Container Delivery Route

This study formulates the operational objectives and constraints within a mathematical model. The mathematical model for this study is as follows:

Index:

i : Origin location index; $i = 0$ is a depot, $i = 0, 1, 2, \dots, N$

j : Destination location index; $j = 0$ is a depot, $j = 0, 1, 2, \dots, N$

r : Route index; $r = 1, 2, \dots, N_r$

t : Tour index; $t = 1, 2, \dots, N_t$

k : Vehicle index; $k = 1, 2, \dots, K$

Parameters:

CIF : Full container inbound task set

COF : Full container outbound task set

CIE : Empty container inbound task set

COF : Empty container outbound task set

C : Tasks set; where $C = C_{IF} \cup C_{OF} \cup C_{IE} \cup C_{OE}$

N : $C \cup \{0\}$

V_k : Vehicle speed k

H : Planning horizons time

$D_{r,t}$: Number of demand nodes of the route r and tour t

$wp_{r,t}$: Service time of the route r and tour t

$wt_{r,t}$: Travel time of the route r and tour t

Variable:

N : Set of nodes

NK : Number of vehicles

NR_t : Number of routes on the tour t

w_i^k : Time when vehicle k to start service at node i

wp_i : Service time at node i

$wt_{i,j}$: Travel time from node i to node j

w_{tct} : Total tour completion time

Variable Decision:

$$x_{ij} = \begin{cases} 1, if\ vehicle\ k\ visits\ node\ j\ after\ node\ i \\ 0, if\ not \end{cases} \tag{1}$$

$$z_{ij} = \text{Travel start time from node } i \text{ to node } j \tag{2}$$

$0j$ is the trip from node 0 (garage) to another node (i, j) ϵ N

$i0$ is the trip of all nodes (i, j) ϵ N to node 0 (garage)

Objective Function

Eq. (3) defines the objective function as follows:

$$min\ f_1 = \sum_{i \in N} x_{0i} \tag{3}$$

This function quantifies the total number of vehicles departing from node 0 (the garage depot) and aims to minimize the overall number of tours required in the network.

Eq. (4) is expressed as:

$$min\ f_2 = \sum_{i.j \in N,} z_{i0} - z_{0j} \tag{4}$$

Where z_{i0} represents the departure time on the final route arriving at node 0, and z_{0j} denotes the departure time on the initial route departing from node 0. Minimizing f_2 effectively reduces the total operating time across all tours.

Constraints:

$$\sum_{i \in N,} x_{ij}^k = 1, k \in K \tag{5}$$

$$\sum_{(i,j) \in N} \sum_{k \in K} x_{ij}^t = 1, \forall\ i \in C \tag{6}$$

$$\sum_{(i,j) \in N} x_{ij}^t = \sum_{n+i,j \in N} x_{n+i,j}^t, 1, \forall\ i \in C, \forall\ t \in N_t \tag{7}$$

$$\sum_{j \neq i, j \in N} x_{ij} = \sum_{j \neq i, j \in N} x_{ji}, 1, \forall\ i \in N \tag{8}$$

$$\sum_{i \in N} x_{ir}^t - \sum_{j \in N} x_{rj}^t = 0, \forall\ t \in N_t \tag{9}$$

$$a_i \leq w_i^k \leq b_i, \forall\ i \in N \tag{10}$$

$$w_{tct} \leq H, \forall H = 8\ hours \tag{11}$$

$$w_{tct} = \sum_{(i,j)\in N} wp_{ij}x_{ij} + wt_{ij}x_{ij}, \forall\ t \in N_t \tag{12}$$

$$x_{ij}^t \in \{0,1\}, \forall t \in N_t, (i,j) \in E \tag{13}$$

The proposed model incorporates the following constraints. Eq. (5) enforces that, for each route $k \in K$, the sum of decision variables x_{ij}^k over all nodes i∈ N equals one, thereby ensuring that each route originates from depot 0. Eq. (6) requires that each container $i \in C$ is assigned exactly once by summing x_{ij}^t over all arcs and vehicles. Eq. (7) further stipulates that for every container $i \in C$ and each tour $t \in N_t$, the number of assignments for pick-up equals that for the corresponding delivery, thus ensuring that paired transport requests are served by the same vehicle. Flow conservation is maintained by Eq. (8), which guarantees that, for each node i∈ N, the number of departures equals the number of arrivals.

Eq. (9) reinforces route continuity by ensuring that, after service, a vehicle immediately proceeds to the next node. Temporal restrictions are enforced by Eq. (10), which bounds the service start time w_i^k at node i within the limits a_i and b_i,. Furthermore, Eq. (11) restricts the total travel completion time w_{tct} to a maximum of eight hours, the predetermined planning horizon. Eq. (12) defines w_{tct} as the total time required by a vehicle to complete its tour, calculated by summing both the service time and travel time across all arcs. Finally, Eq. (13) constrains x_{ij}^t to binary values, ensuring that decisions regarding arc selections remain discrete. Collectively, these constraints ensure both the feasibility and the optimality of the routing operations under the VRPPD-TW framework.

Furthermore, an optimization framework based on a sequential insertion algorithm was developed in conjunction with the mathematical model. The mathematical notation of the VRPPD-TW is subsequently solved using the sequential insertion algorithm. The design of the algorithm is developed to address the objective function of the VRPPD-TW mathematical model, considering the entire set of model constraints. It means that the output of the sequential insertion algorithm must comply all the mathematical equations. Fig. 3, illustrates the flowchart outlining the sequential insertion algorithm employed in this investigation.

The flowchart procedure is systematically translated into a computer program, developed using the Python programming language to serve as a computational tool for this study. The software algorithm iteratively evaluates combinations of transportation tours, halting once no further tours satisfy the constraint functions, such as time windows or operational limits. Demonstrating computational efficiency, the software processes input data and delivers optimal solutions within an average runtime of less than 5 minutes. Access to the complete VRPD-TW software is provided via the corresponding link. (https://bit.ly/VRPPD_Planning_Route_ContainerTruck).

The developed program was validated using actual data by comparing manually computed results with those generated by the model. This validation process confirmed that the computational outputs were consistent with the manual calculations, thereby verifying the program's robustness and suitability for determining the overall solution in this study.

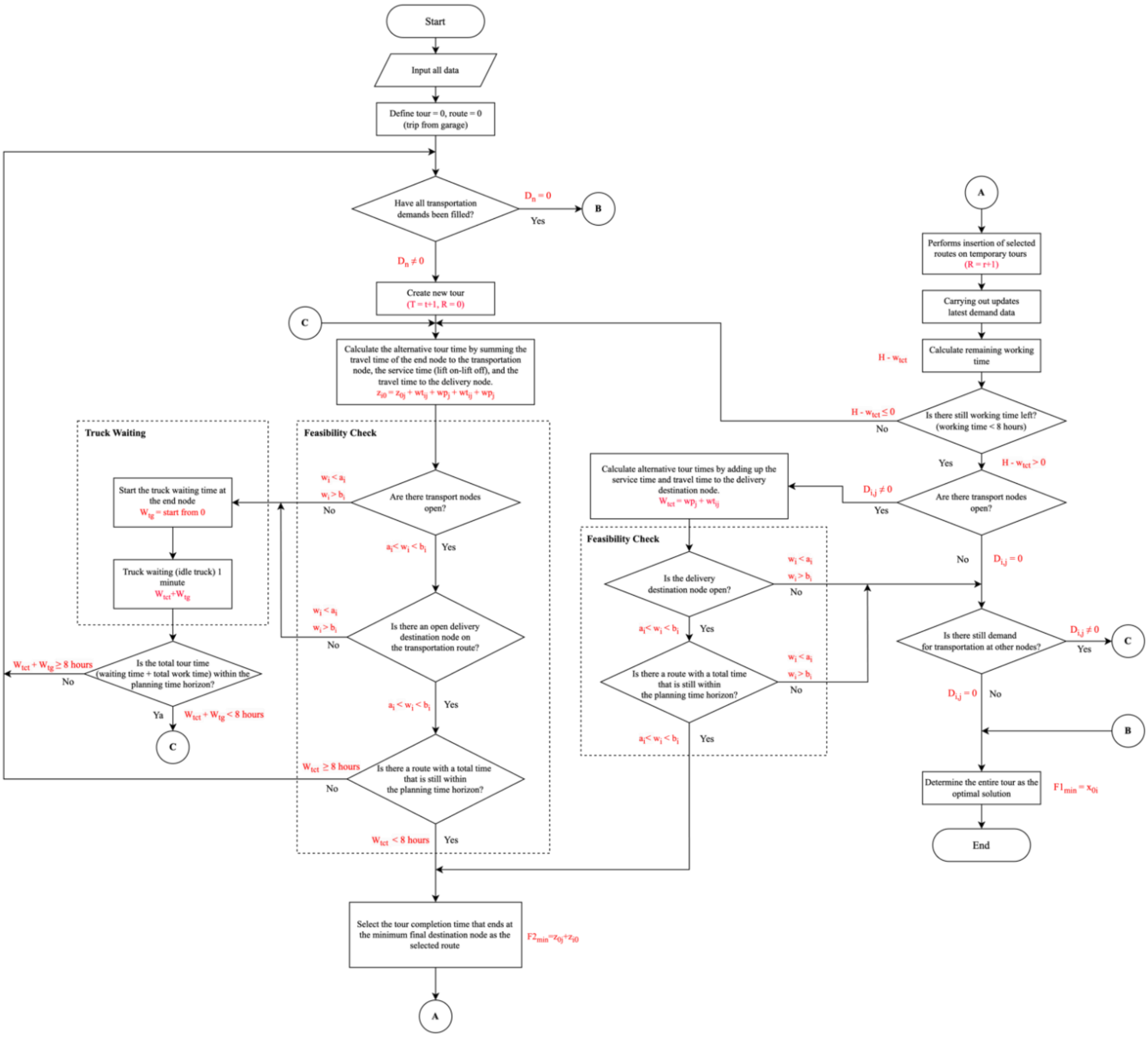

Fig. 3. Sequential Insertion Algorithm of VRPPD-TW

3. Results and Discussion

This VRPPD-TW model is designed with the objective of minimizing the number of tours (or vehicles) required to satisfy container repositioning demands, as defined by the formulated mathematical notation. To achieve this, the sequential insertion algorithm is employed, which optimally integrates nodes into route combinations to determine the most efficient number of tours. The generation of routes and tours is influenced by the combinations of transportation and delivery location points. As the number of visitable locations increases, the number of potential route combinations expands, thereby enhancing the solution's accuracy, albeit with increased computational complexity. This model implements a soft time window system, where, in the absence of active pickup or delivery nodes, the model pauses and rechecks the status of these nodes every minute. This process iterates continuously until a valid repositioning request is detected.

3.1. Numerical Examples

Prior to data processing, it is imperative to collect data on routing structure, the time windows at visited locations, the inter-location distance matrix, and the daily demand for container repositioning. The routing structure additionally incorporates two supplementary depots (situated in Cakung and Sunter), two external container storage facilities (also in Cakung and Sunter), and a port terminal. The container yard in Sunter operates continuously to manage both the container procurement process at the plant and the repositioning of containers for export and import activities. Nevertheless, despite this 24-hour operation, truck access to the container yard is restricted to the period from 00:00 to 05:00, with a maximum of 60 container lift-on and lift-off operations permitted during this window. Table 1. details these time restrictions and the operational processes for container pickup and delivery. Consequently, given the limited access for trailer trucks, this study focuses on the night shift time horizon, from 23:00 to 07:00, at an average truck speed of 40 km/h, and corresponding to an 8-hour planning period.

Table 1. Location and Time Windows

Node	Location point (node)	Pick-Up	Delivery	*Time interval*	
				Open	*Closed*
0	Garage trucking company	-	-	24 hours	
1	Container Yard Company	√	√	00.30	05.00
2	Sunter Container Depot	√	√	24 hours	
3	Cakung Container Depot	√	√	24 hours	
4	Sunter Container Yard	√	√	24 hours	
5	Cakung Container Yard	√	√	24 hours	
6	Terminal Port	√	√	24 hours	

In this study, the company's container delivery demand in 2022 totaled 10,755 containers. This annual requirement was disaggregated into daily repositioning demands for each location, as detailed in Table 2. The container repositioning network comprises both import and export routes. Import operations include inbound full container routes (r_{41}, r_{51}, r_{61}, r_{64}, and r_{65}) and outbound empty container routes (r_{12} and r_{13}), while export operations involve inbound empty container routes (r_{21} and r_{31}) and outbound full container routes (r_{14}, r_{15}, r_{16}, r_{46}, and r_{56}).

Table 2. Daily Demand for Container Repositioning

Delivery		Transport		Route (r_{ij})	Container Demand
Node (i)	Location name	Node (i)	Location name		
1	Company Container Yard	2	Sunter Container Depot	r_{12}	2
		3	Cakung Container Depot	r_{13}	2
		4	Sunter External Container Yard	r_{14}	1
		5	Cakung External Container Yard	r_{15}	1
		6	Terminal port	r_{16}	7
			Total		13
2	Sunter Container Depot	1	Company Container Yard	r_{21}	11
		3	Cakung Container Depot	r_{23}	0
		4	Sunter External Container Yard	r_{24}	0
		5	Cakung External Container Yard	r_{25}	0
		6	Terminal port	r_{26}	0
3	Cakung Container Depot	1	Company Container Yard	r_{31}	11
		2	Sunter Container Depot	r_{32}	0
		4	Sunter External Container Yard	r_{34}	0
		5	Cakung External Container Yard	r_{35}	0
		6	Terminal port	r_{36}	0
			Total		11
4	Sunter External Container Yard	1	Company Container Yard	r_{41}	1
		2	Sunter Container Depot	r_{42}	0
		3	Cakung Container Depot	r_{43}	0
		5	Cakung External Container Yard	r_{45}	0
		6	Terminal port	r_{46}	1
			Total		2

Delivery		Transport		Route (r_{ij})	Container Demand
Node (i)	Location name	Node (i)	Location name		
5	Cakung External Container Yard	1	Company Container Yard	r_{51}	1
		2	Sunter Container Depot	r_{52}	0
		3	Cakung Container Depot	r_{53}	0
		4	Sunter External Container Yard	r_{54}	1
		6	Terminal port	r_{56}	1
		Total			2
6	Terminal port	1	Company Container Yard	r_{61}	3
		2	Sunter Container Depot	r_{62}	0
		3	Cakung Container Depot	r_{63}	0
		4	Sunter External Container Yard	r_{64}	1
		5	Cakung External Container Yard	r_{65}	1
		Total			5

Table 3, provides the distance matrix for each node. These distances were converted into corresponding travel times for container delivery trucks, assuming a constant speed of 40 km/h.

Table 3. Travel Distance Matrix

Node	Travel distance matrix (km)						
	0	**1**	**2**	**3**	**4**	**5**	**6**
0	0	8.1	6.4	18	7	13.3	5.2
1	8.1	0	7.7	14.1	8.1	17	12.4
2	6.4	7.7	0	14.5	2.7	15.9	11.3
3	18	14.1	14.5	0	15	5.1	16.4
4	7	8.1	2.7	15	0	15.9	11.3
5	13.3	17	15.9	5.1	15.9	0	11.7
6	5.2	12.4	11.3	16.4	11.3	11.7	0

Following the collection of all requisite data in accordance with the variables and parameters of the formulated mathematical model, computational evaluations were conducted using a sequential insertion algorithm. These computational outcomes were then validated through manual calculations. For example, the results for Tour 1 exhibited complete agreement with the manual analysis in terms of the node visitation sequence and the working time requirement, which encompasses both travel and service durations at each node. Manual calculations (Tour 1) using Microsoft Excel resulted in the route n0-n6-n4-n6-n5-n6-n1-n2-n1-n2-n1-n4-n1-n6-n1-n6-n0 which was carried out in 15 iterations. This compatibility confirms the validity of the computational program, and the verified tool was subsequently used to derive the study's overall results. The optimal route cost calculations obtained from the computational program are presented in Table 4.

Table 4. Validation of Computational Result

Tour	Route	Distance (km)	Working time (minutes)
1	n0-n6-n4-n6-n5-n6-n1-n2-n1-n2-n1-n4- n1-n6-n1-n6-n0	135.4	366
2	n0-n6-n1-n6- n2-n1-n6-n2- n1-n6-n2-n1- n6-n2-n1-n6- n2-n1-n0	143.2	364
3	n0-n5-n1-n6-n2-n1-n3-n1-n3-n1-n5-n0	148.4	282
4	n0-n3-n1-n2- n1-n2-n1-n2- n1-n2-n1-n3- n1-n0	130	295
5	n0-n3-n1-n3- n1-n3-n1-n3- n1-n3-n1-n0	153	267
6	n0-n3-n1-n3- n1-n0	68.4	110

The use of this VRPPD-TW model is still focused on a limited situation (the pick-up and delivery process occur at fixed nodes), where the demand parameters and travel times do not change significantly. Therefore, sensitivity analysis is not performed in this study, as changes in parameters would not significantly affect the results. However, for future research, this model should involve sensitivity analysis to understand the reliability and stability of the model.

Based on the routing results presented in Table 4, the mechanism of sequential insertion in addressing container repositioning is elucidated. All processes are systematically computed using the established model algorithm illustrated in Fig. 3. Containers are incorporated into the solution incrementally, adhering to a predetermined order or priority sequence. In particular, algorithm modifications are performed. This sequence is guided by specific criteria, including container requests, time windows, and proximity to the target location. At each step, the algorithm rigorously evaluates all possible positions or actions (determining optimal repositioning points). This modification process makes this approach able to produce a more robust initial solution while remaining adaptable to data changes.

Table 5. Performance Comparison of Existing Tours versus Research Model Outputs

Indicator	Existing	Research result
Number of tours	37	6
Number of Vehicles/Day	12	6

Table 5, demonstrates that the tour and route configuration produced by the computational program in this study is markedly superior. This result is consistent with the study by Lai et al. (2013), which discusses the use of meta-heuristic methods to address container repositioning problems, resulting in improved operational efficiency in terms of both the number of tours and the number of vehicles used. This research generating only six tours compared to the existing 37 tours. This significant difference is attributable to the fact that the company’s current approach does not incorporate fleet sizing to adequately meet the daily container repositioning demand. In contrast, the proposed model optimizes vehicle usage, reducing the average daily truck requirement from 12 to 6 a 50% reduction. This efficiency improvement largely stems from the limitations of the current intuitive route determination method, which restricts each truck to a maximum of two tasks and confines container repositioning management to the Sunter container yard.

The configuration of routes and tours in the model is determined by the combination of pickup and delivery points. As the number of visited points increases, the number of potential route combinations grows, necessitating a higher degree of accuracy in the computational process. This precision directly influences the reliability of the route calculations. In this study, the sequential insertion algorithm was implemented in Python, yielding an average processing time of 10 seconds for a scenario involving six pickup and delivery nodes and 30 route combinations. It is anticipated that variations in the number of nodes and route combinations will correspondingly affect the computational processing time and the number of iterations required.

The final outcomes of route and tour generation through the VRPPD-TW model significantly impact operational cost efficiency. For instance, vehicles (truck) rental charge are directly proportional to the number of tours generated by the model. Empirical computation (from the model's implementation) reveal that the computational program produced a solution requiring only 6 trucks (represented as the number of tours), compared to the current average daily usage of 12 trucks. This indicates that the model can directly contribute to a 50% reduction in operational costs, demonstrating its potential for substantial cost savings in logistics operations.

Key findings that differentiate this model from previous LNS approaches in container repositioning (Zhang et al., 2020), are evident in several aspects. Sequential Insertion effectively overcomes the susceptibility of LNS to local optima by systematically integrating elements (e.g., containers or routes) and exploring a broader solution space. It reduces the computational complexity associated with searching large neighbourhoods by focusing on incremental solution construction, thereby lowering computational demands. Moreover, it addresses the issue of imbalanced workload by optimizing task distribution across resources, considering constraints such as capacity and time windows. Unlike LNS, which heavily relies on the quality of the initial solution, Sequential Insertion generates robust initial solutions by prioritizing cost-effective insertions, allowing for further refinement. Lastly, its adaptability to dynamic or real-time constraints, such as sudden changes in container availability or routing conditions, ensures recalculated and adjusted solutions, enhancing overall efficiency.

This model exhibits several limitations. The algorithm primarily focuses on optimizing the number of vehicles, represented by the number of tours, without accounting for the balance of total working time across the generated tours. Additionally, the model does not account for queue times; if multiple trucks arrive at the same location simultaneously, dynamic waiting times may occur within the queue, which should be addressed in future model development. From a computational perspective, the software output restricted to optimizing a maximum of 20 nodes and 360 route combinations, limiting its applicability and scalability to larger networks. Moreover, the software output is restricted to providing a sequence of visit routes, without offering detailed scheduling information.

4. Conclusion

This study demonstrates that a mathematical model for the Vehicle Routing Problem with Pickup and Delivery and Time Windows (VRPD-TW), coupled with a sequential insertion algorithm, can be effectively employed to optimize route selection for export-import container repositioning. The model is designed for contexts with time windows, a homogeneous fleet, and a single product type (containers), allowing simultaneous lift-on and lift-off at the same location. The computational program developed based on this model produced an optimal configuration of six tours—a significant improvement over current practices, resulting in a 50% reduction in the number of vehicles required. This outcome underscores the potential of systematic optimization to enhance route efficiency and resource utilization in container repositioning operations.

Although the model's performance is influenced by the number of visited locations and corresponding route combinations, it provides a robust framework for similar VRPD-TW scenarios. Future work may focus on scaling the model for larger networks and integrating further complexities, such as heterogeneous fleets and dynamic queuing, to further improve logistical efficiency. The proposed sequential insertion algorithm and VRPPD-TW framework demonstrate significant potential for applications across diverse industries, including supply chain optimization, urban logistics, automotive industry, and healthcare delivery systems. More specifically, industries that involve import-export processes using containers in their business operations. By addressing pick-up and delivery routing challenges within constrained environments, the model's adaptability can enhance efficiency in real-world scenarios. Future research could expand on this foundation by incorporating heterogeneous fleets, dynamic queuing mechanisms, and additional constraints such as varying service priorities or stochastic demands. Furthermore, testing the model's scalability in larger networks would provide valuable insights into its robustness and practical viability for complex operational landscapes.

Author Contribution: All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

Alfandari, L., Davidovic, T., Furini, F., Ljubic, I., Maras, V., & Martin, S. (2019). Tighter MIP models for Barge Container Ship Routing. *Omega*, *82*, 38–54. https://doi.org/10.1016/j.omega.2017.12.002

Armbrust, P., Maier, K., & Truden, C. (2022). *Sweep Algorithms for the Vehicle Routing Problem with Time Windows* (pp. 135–144). https://doi.org/10.1007/978-3-031-22039-5_11

Arvianto, A., Perkasa, D. S., Budiawan, W., Laksosno, P. W., & Saptadi, S. (2015). Vehicle routing problem modelling to minimize a number of Vehicle by considering heterogenous fleet vehicle. *Proceedings of the Joint International Conference on Electric Vehicular Technology and Industrial, Mechanical, Electrical and Chemical Engineering (ICEVT & IMECE)*, 380–388. https://doi.org/10.1109/ICEVTIMECE.2015.7496701

Bawono, A. T., Rumambi, F. J., & Rante, J. Z. (2019). Pengaruh Integrasi Logistik dan Kinerja Rantai Pasok Terhadap Kecepatan Distribusi Barang dan Dampaknya Pada Pertumbuhan Perusahaan PT. Yicheng Logistics. *Jurnal Manajemen Dan Bisnis*, *5*(2), 15–24. https://repository.ibmasmi.ac.id/assets/files/content/f_0434_20220826100359.pdf

Deng, A., Mao, C., & Zhou, Y. (2009). Optimizing Research of an Improved Simulated Annealing Algorithm to Soft Time Windows Vehicle Routing Problem with Pick-up and Delivery. *Systems Engineering - Theory & Practice*, *29*(5), 186–192. https://doi.org/10.1016/S1874-8651(10)60049-X

Desrosiers, J., Dumas, Y., & Soumis, F. (1986). A Dynamic Programming Solution of the Large-Scale Single-Vehicle Dial-A-Ride Problem with Time Windows. *American Journal of Mathematical and Management Sciences*, *6*(3–4), 301–325. https://doi.org/10.1080/01966324.1986.10737198

Euchi, J., & Sadok, A. (2021). Hybrid genetic-sweep algorithm to solve the vehicle routing problem with drones. *Physical Communication*, *44*, 101236. https://doi.org/10.1016/j.phycom.2020.101236

Fazi, S., Fransoo, J. C., Van Woensel, T., & Dong, J.-X. (2020). A variant of the split vehicle routing problem with simultaneous deliveries and pickups for inland container shipping in dry-port based systems. *Transportation Research Part E: Logistics and Transportation Review*, *142*, 102057. https://doi.org/10.1016/j.tre.2020.102057

Febriyanti, D. E., Primadasa, R., & Bhakti Sutono, S. (2022). Determination of Distribution Routes Using the Saving Matrix Method to Minimize Shipping Costs at Pt. Sukun Transport Logistics. *Spektrum Industri*, *20*(1), 79–90. https://doi.org/10.12928/si.v20i1.18

Hasibuan, A., Banjarnahor, A. R., Sahir, S. H., Cahya, H. N., Nur, N. K., Purba, B., SN, A., Prasetio, A., Ardiana, D. P. Y., Purba, S., & Mardia. (2021). *Manajemen Logistik dan Supply Chain Management* (1st ed.).

Joubert, J., & Claasen, S. (2006). A sequential insertion heuristic for the initial solution to a constrained vehicle routing problem. *ORiON*, *22*(1). https://doi.org/10.5784/22-1-36

Kurniawan, I. S., Susanty, S., & Adianto, H. (2014). Usulan Rute Pendistribusian Air Mineral Dalam Kemasan Menggunakan Metode Nearest Neighbour dan Clarke & Wright Savings (Studi Kasus di PT. X Bandung). *Reka Integra, Jurnal Online Institut Teknologi Nasional*, *1*(4), 125–136. https://www.academia.edu/118943447/Usulan_Rute_Pendistribusian_Air_Mineral_Dalam_Kemasan_Menggunakan_Metode_Nearest_Neighbour_dan_Clarke_and_Wright_Savings_Studi_Kasus_di_PT_X_Bandung_

Kusumastuti, D., & Sugiama, A. G. (2017). *Manajemen Logistik Organisasi Publik (2nd Ed.)* (2nd ed.). Universitas Terbuka.

Lai, M., Paola, A., Co-Advisor, Z., & Battarra, M. (2013). *Models and algorithms for the empty container repositioning and its integration with routing problems*. https://iris.unica.it/retrieve/e2f56ed8-3aef-3eaf-e053-3a05fe0a5d97/Lai_PhD_Thesis.pdf

Lau, H. C., & Liang, Z. (2002). Pickup and Delivery with Time Windows: Algorithms and Test Case Generation. *International Journal on Artificial Intelligence Tools*, *11*(03), 455–472. https://doi.org/10.1142/S0218213002000988

Meng, L., Ge, H., Wang, X., Yan, W., & Han, C. (2023). Optimization of ship routing and allocation in a container transport network considering port congestion: A variational inequality model. *Ocean & Coastal Management*, *244*, 106798. https://doi.org/10.1016/j.ocecoaman.2023.106798

Nono, V., Sofitra, M., & Wijayanto, D. (2020). Penyelesaian Capacitated Vehicle Routing Problem Dengan Menggunakan Algoritma Sweep Untuk Penentuan Rute Distribusi Untuk Depo Pt. Abc Kubu Raya. *Jurnal Teknik Industri Universitas Tanjungpura*, *4*(2), 232–238. https://industri.teknik.untan.ac.id/jurnal

Prasetyo, W., & Tamyiz, M. (2017). Vehicle Routing Problem Dengan Aplikasi Metode Nearest Neighbor. *Journal of Research and Technology*, *3*(2). https://doi.org/10.55732/jrt.v3i2.263

Saragih, N. I., & Turnip, P. (2024). Tabu Search Algorithm for Solving a Location-Routing-Inventory Problem. *Spektrum Industri*, *22*(2), 155–162. https://doi.org/10.12928/si.v22i2.234

Sitek, P., Wikarek, J., Rutczynska-Wdowiak, K., Bocewicz, G., & Banaszak, Z. (2021). Optimization of capacitated vehicle routing problem with alternative delivery, pick-up and time windows: A modified hybrid approach. *Neurocomputing*, *423*, 670–678. https://doi.org/10.1016/j.neucom.2020.02.126

Suryani, S., Kuncoro, K. R., & Fathimahhayati, L. D. (2018). Perbandingan Penerapan Metode Nearest Neighbour Dan Insertion Untuk Penentuan Rute Distribusi Optimal Produk Roti Pada Ukm Hasan Bakery Samarinda. *PROFISIENSI: The Journal of the Industrial Engineering Study Program*, *6*(1), 41–49. https://www.journal.unrika.ac.id/index.php/jurnalprofisiensi/article/view/1456

Toth, P., & Vigo, D. (2015). *Vehicle Routing: Problems, Methods, and Applications, Second Edition* (2nd ed.). Society for Industrial and Applied Mathematics (SIAM).

Vidovic, M., Radivojevic, G., & Rakovic, B. (2011). Vehicle routing in containers pickup up and delivery processes. *Procedia - Social and Behavioral Sciences*, *20*, 335–343. https://doi.org/10.1016/j.sbspro.2011.08.039

Wang, S. (2014). A novel hybrid-link-based container routing model. *Transportation Research Part E: Logistics and Transportation Review*, *61*, 165–175. https://doi.org/10.1016/j.tre.2013.11.006

Widyawati, N., Merciana, D., & Kalangi, M. H. E. (2020). Moda Transportasi Darat Dan Kualitas Layanan Jasa Terhadap Kelancaran Arus Container Di Depo. *Jurnal Baruna Horizon*, *3*(2), 230–241. https://doi.org/10.52310/jbhorizon.v3i2.43

Wulandari, C. B. K. (2020). Penentuan Rute Distribusi Menggunakan Metode Nearest Neighbors dan Metode Branch and Bound Untuk Meminimumkan Biaya Distribusi di PT. X. *Jurnal Optimasi Teknik Industri (JOTI)*, *2*(1), 7. https://doi.org/10.30998/joti.v2i1.3848

Zhang, R., Huang, C., & Wang, J. (2020). A novel mathematical model and a large neighborhood search algorithm for container drayage operations with multi-resource constraints. *Computers & Industrial Engineering*, *139*, 106143. https://doi.org/10.1016/j.cie.2019.106143