

Decision Making Model for Frozen Distribution using Cross-dock

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ABSTRACT

Within the cross-dock facility, suppliers transport goods on pallets; however, there are instances when the received amount does not align with the allocation demand, resulting in either surplus or shortage. This situation raises the challenge of determining the appropriate customer to handle the excess or shortfall while also addressing any potential penalties. In the case of frozen deliveries, time sensitivity is of utmost importance, necessitating swift and efficient procedures. However, Ho Chi Minh City's dynamic environment poses challenges when delivery schedules deviate, making it necessary to accept such variations. The problem also involves optimizing vehicle allocation and managing early or late deliveries, along with over-deliveries or under-deliveries. The objective of this study is to create an enhanced schedule and strategy for vehicle allocation that effectively reduces three cost components: transportation expenses, penalties associated with untimely deliveries, and fines for inaccuracies in product quantities. A robust model will be introduced to balance these costs effectively, providing valuable insights for frozen product distribution. The model was initially tested on a sample problem using the Trial-and-Error method with CPLEX. Given the large data set and time constraints in real-world scenarios, Simulated Annealing is used to optimize the solution faster, making it more practical for implementation.

Keywords: *crossdocking, distribution decision model, optimization, penalty cost*

1. INTRODUCTION

Significant progress has been made in the domain of goods distribution, focusing primarily on vehicle routing and precise delivery scheduling. Dantzig and Ramser (1959) made a notable contribution to the field by introducing the Truck Dispatching Problem, which served as a significant milestone in the advancement of vehicle routing research. Since then, studies have highlighted the complex nature of goods distribution, showing it is influenced by various factors like vehicle capacity and time constraints, which heavily impact the process. Acevedo et al., 2023 introduced a cross-dock system integration model to improve the efficiency of goods distribution from factories to markets by minimizing logistics costs. The authors considered time frames for picking and delivering, heterogeneous and limited vehicle capacity, as well as parameters such as waiting times and loading times. In the same year, Bavar et al., 2023 also studied a routing model for time-constrained vehicles. The goal of the study included minimizing transportation costs while ensuring timely receipt of products by the customer. It can be seen that recent studies still focus on costs and delivery times. Meanwhile, the number of delivered goods, a possible issue in a cross-dock environment, has received less attention from researchers. Therefore, this research aims to optimize delivery quantity while minimizing costs and ensuring on-time delivery, to improve customer experience.

The choice of warehouse utilized in logistics can significantly impact the effectiveness of the supply chain. In this context, a cross-dock warehouse is selected, focusing on minimal or no inventory storage. Rather than functioning as a storage facility, it operates as a rapid transfer hub where goods are received and promptly transferred to outgoing trucks for transportation. Current developments in goods

allocation have indicated a noticeable transition from conventional warehousing to the cross-dock model, attracting significant interest in both academic and business spheres. Studies by Theophilus *et al.* (2019), Mukherjee *et al.* (2022), and Akkerman *et al.* (2022) have traced the model's development back to the 1980s, though it wasn't until 2004 that its full potential started to be realized. The core principle of the cross-dock model is transshipment. This principle avoids the need to hold large inventories. As a result, it is a strong strategy in supply chain management. This approach offers several advantages, including lower inventory holding costs, faster order fulfillment, and improved overall efficiency. As businesses continue to navigate complex distribution challenges, the cross-dock model has become a key strategy for balancing cost savings with excellent service delivery.

In the ever-changing landscape of goods distribution, balancing the amount of goods received with the amount scheduled for delivery is often challenging. It's common for customers to receive either more or fewer goods than initially planned. In highly populated urban regions, where congested roadways and unpredictable traffic are commonplace, guaranteeing punctual deliveries becomes even more arduous. These logistical hurdles can sometimes make it impossible to stick to predetermined schedules. When there are discrepancies in goods quantities or delivery times, suppliers may face penalties, though these are usually imposed only if deviations exceed an acceptable range. Beyond these issues, distribution operations are further complicated by transportation costs, which are influenced by factors like order consolidation, delivery route sequencing, and vehicle capacity. The optimization of these factors is essential, as it plays an essential role in cost control and enhancing the overall efficiency of operations.

The primary aim of this research is to create a thorough model designed to support decision-making in the field of goods distribution. This model focuses on the complex cost landscape related to these operations, highlighting three key areas: transportation expenses, penalties for late or early deliveries, and fines due to discrepancies in the amount delivered. By exploring these intricate aspects, this study seeks to establish a systematic framework that enables stakeholders to make well-informed decisions, enhance their distribution processes, and achieve a balance between cost efficiency and high-quality service.

2. LITERATURE REVIEW

To gain a comprehensive understanding of this study, it is essential to examine the concepts of cross-docking, vehicle routing, and the Simulated Annealing algorithm employed in this research. The majority of existing literature predominantly emphasizes factors such as time constraints and vehicle routing efficiency. In contrast, this study distinguishes itself by integrating these elements and introducing additional considerations aimed at optimizing order quantities for customers. This multifaceted approach contributes to a more holistic understanding of the complexities involved in logistics and distribution.

The choice of logistics model greatly impacts supply chain efficiency, and the cross-dock model has become increasingly popular. Unlike traditional warehousing, cross-docking minimizes or eliminates storage by acting as a quick

transfer hub, where goods are swiftly moved from arriving to departing trucks. This model has gained attention in both academic and business circles, with its roots dating back to the 1980s (Theophilus *et al.*, 2019; Mukherjee *et al.*, 2022; Akkerman *et al.*, 2022).

Cross-docking offers several key advantages. It reduces warehousing costs by cutting down on storage, labor, and transportation expenses (Van Belle *et al.*, 2012; Marcoux *et al.*, 2005). Additionally, it minimizes the need for storage space, lowers the risk of damaged goods, and prevents overstocking (Van Belle *et al.*, 2012). The model also speeds up supply chain operations, reducing lead times and enhancing customer satisfaction (Ye *et al.*, 2018). Cross-docking improves control over delivery schedules, ensuring timely and reliable service (Hosseini *et al.*, 2014). These benefits – cost savings, speed, and control – make cross-docking particularly effective for product delivery, especially for frozen foods.

These problems in cross-docking warehouses are still being raised and solved by researchers. The complexities associated with cross-dock deliveries were underscored by Yu *et al.* (2012), highlighting various challenges such as time limitations, vehicle routing, capacity restrictions, as well as the need to meet delivery deadlines; all with the ultimate objective of cost optimization. Dawande *et al.* (2006) studied conflicts in a supply chain where manufacturers and distributors have separate schedules, leading to inefficiencies in cost and time. Manufacturers prioritize nearby customers to reduce setup time, while distributors focus on distant customers to minimize delivery delays, causing conflicts in customer and inventory costs. The authors proposed three scenarios: one party imposing its schedule, one adapting to the other, and collaboration between both. Their results showed that collaboration minimized costs. Similarly, Kuo *et al.* (2010) addressed temperature control in food distribution, recommending multi-temperature containers to prevent spoilage and ensure freshness throughout the supply chain. Both studies emphasize the importance of coordination to improve overall performance.

There are quite a few studies focusing on the issue of vehicle routing for cross-dock warehouses. Birim (2016) examined a logistics issue where goods are picked up from suppliers and sent to a cross-dock for consolidation before final delivery, using heterogeneous vehicles with fixed routes starting and ending at the cross-dock. Yu *et al.* (2016) introduced a multi-period cross-dock distribution problem that addressed issues such as multiple products and order consolidation over time, aiming to reduce transportation, inventory, and penalty costs. Ahkamiraad and Wang (2018) proposing a model to reduce both transportation and fixed costs by optimizing vehicle routing for multiple cross-docks, while Gunawan *et al.* (2021) incorporated reverse logistics to improve competitiveness by minimizing overall transportation and operational costs. Goodarzi *et al.* (2020) advanced this by introducing an optimization model that allows split deliveries and assigns time windows, focusing on minimizing operational costs and deviations in scheduled pickup and delivery times. Finally, Xi *et al.* (2020) tackled the cross-dock truck scheduling problem, emphasizing minimizing penalty costs and scheduling conflicts through a two-stage optimization model, improving overall system efficiency. In logistics, optimizing vehicle routes to serve

multiple customers enhances cost-efficiency and sustainability. Lee *et al.* (2006) pioneered this with a method to minimize transportation costs for pickup and delivery, evolving from an integer programming model to a more efficient tabu search algorithm that separated routing phases to avoid delays at cross-docks. Building on this, Gunawan *et al.* (2021) applied advanced algorithms to achieve a 12.6% cost reduction in cross-docking logistics. The model in this study also considers the vehicle routing problem for distributing goods from cross-dock warehouse.

Meeting customer demand is a critical element and a key priority in distribution problems. Every stage of the distribution process is aimed at fulfilling demand and enhancing the customer experience. Liu and Zhang (2023) introduced a novel optimization model to address distribution challenges driven by unstable consumer demand, influenced by environmental and social factors. Their study included a trapezoidal fuzzy time window constraint, as well as varying cost and demand scenarios. The findings indicate that the flexible delivery time management strategy effectively balances vehicle optimization with the timely fulfillment of orders. Avishan *et al.* (2025) proposed an adaptive optimization method for addressing the multi-cycle production and distribution planning problem for perishable goods. Their approach incorporates a folded horizon model to re-optimize plans based on actual demand. The results showed significant improvements in the objective function values—covering production, setup, activation, and operating costs—compared to traditional optimization models, all while ensuring demand fulfillment. Efforts to meet customer demand often lead to cost-related conflicts, requiring suppliers to carefully balance customer requirements with cost optimization across multiple factors. The vehicle routing problem is often combined with other problems in previous studies. Rahimi *et al.* (2014) proposed a dual-objective model, minimizing total operating costs (involving transportation cost) for perishable inventory and minimizing total delays. Their study considered a joint inventory and routing problem. They then investigated whether this optimization has any impact on customer satisfaction. The results showed that a small increase in cost can lead to a nearly 40% increase in customer satisfaction. Furthermore, total cost and number of delays appear to be inversely proportional if the latter is too large. The model suggests that one should not try to reduce delays to an absolute minimum because costs can increase uncontrollably. While cost optimization and customer experience are trade-offs in Rahimi's study, this study shows that in some contexts, optimizing service level can simultaneously optimize cost. This opens a new approach where businesses can optimize both factors. Nguyen *et al.* (2016) focuses on solving the stochastic vehicle routing problem with time windows (VRPTW) by Satisficing Measure Approach (SMA) that mitigates the dissatisfaction experienced by the customers. Both papers consider customer satisfaction: Rahimi *et al.* (2014) accepts back orders and inventory, Nguyen *et al.* (2016) gives a formula to calculate customer satisfaction based on inventory shortage due to vehicle limitation and uncertain demand. Our model considers customer satisfaction by minimizing the penalty cost of delivering more or less than the demand and delivering later or earlier than the customer's desired time.

Several authors have formulated the vehicle routing problem considering time windows, such as Kallehauge *et al.* (2005), Spliet and Gabor (2014), Phan and Kim (2015) ... Kallehauge *et al.* (2005) contributed with mathematical models for vehicle routing with time windows, though challenges persist, driving continued advancements in routing efficiency. Time-based optimization was explored by Spliet and Gabor (2014) with the Time Window Assignment Vehicle Routing Problem (TWAVRP), aiming to reduce travel costs, while Phan and Kim (2015) addressed port congestion with a truck appointment system. Goodarzi *et al.* (2020) introduced a more complex model, incorporating truck scheduling, order splitting, and time-window constraints to further optimize costs. Furthermore, the vehicle routing problem with time windows encompasses a combination of various factors. Gmira *et al.* (2021) addressed a capacitated vehicle routing problem with time windows in an urban network, incorporating variations in travel time across road segments. They employed a multi-objective optimization approach to minimize both the cost and total duration of the routes. Yesodha and Amudha (2022) tackled a more intricate extension of the Vehicle Routing Problem (VRP) referred to as the Multi-Depot Vehicle Routing Problem with Time Windows (MDVRP-TW). This problem involves multiple depots and aims to minimize transportation distances while adhering to specific constraints, such as vehicle capacity and time windows for customer service. To solve this problem, they utilized an enhanced bio-inspired metaheuristic algorithm known as the firefly algorithm. Wang *et al.* (2021) focused on optimizing vehicle routes and transportation costs in collaborative multi-depot pickup and delivery logistics networks. Their approach took into consideration time windows, capacitated vehicles, and travel time variations, while also incorporating environmental considerations.

Yu *et al.* (2012) addressed the issue of vendor selection within a lean procurement system, considering the presence of unreliable information and incorporating a flexible time window for delivery. This mechanism sets earliest (E) and latest (L) delivery times, with lower bounds (LE) and upper bounds (UL). Deliveries that take place prior to the lower limit (LE) or beyond the upper limit (UL) are not accepted, whereas those falling within the range of LE and E or L and UL are acknowledged with a penalty. The authors proposed a modified Fuzzy Multi-Objective Programming model to determine vendor selection and order quantities. They placed emphasis on performance metrics based on time; yet did not offer empirical validation or real-world application of the model.

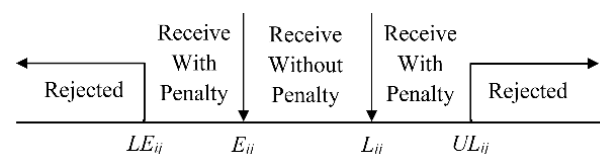


Figure 1 Visual depiction of the time-window.

The complexities associated with cross-dock deliveries were underscored by Yu *et al.* (2012), highlighting various challenges such as time limitations, vehicle routing, capacity restrictions, and the need to meet delivery deadlines, all with the ultimate objective of cost optimization. While extensive research has been conducted on these aspects, there is a

noticeable research gap. Previous studies have not fully integrated and examined the three crucial cost dimensions: transportation expenses, penalties for untimely deliveries, and penalties for incorrect delivery quantities, all with the simultaneous objective of optimization. Consequently, the objective of this study is to address this research gap by introducing a model that adeptly integrates and harmonizes these elements, thereby making a significant contribution to

a more comprehensive and efficient approach to cross-dock distribution.

Table 1 offers a comprehensive overview of the optimization aims present in various publications. Each publication is marked with the specific optimization aim it addresses. This systematic categorization allows for a quick and clear understanding of the diverse optimization objectives covered in the literature.

Table 1 Overview of publications about vehicle routing problem for cross-dock.

Publications	Optimization Aim					
	Transportation costs	Vehicle costs	Vehicle routing schedule	Time windows	Time appointment	Penalty
Kallehauge <i>et al.</i> (2005)	x			x	x	
Lee <i>et al.</i> (2006)	x	x	x			
Yu <i>et al.</i> (2012)				x	x	
Spliet and Gabor (2014)	x		x	x		
Birim (2016)	x	x	x	x		
Yu <i>et al.</i> (2016)	x			x		x
Ahkamiraad and Wang (2018)	x	x	x			
Goodarzi <i>et al.</i> (2020)	x			x	x	x
Xi <i>et al.</i> (2020)	x		x			
Gunawan <i>et al.</i> (2021)	x	x	x	x		
This Study	x	x	x	x	x	x

Table 2 Summary of publications.

Authors	Purpose	Methods	Findings
Dawande <i>et al.</i> (2006)	Minimize customer costs and inventory holding costs	Algorithm for Each Scenario	Costs can be significantly decreased due to collaboration in scheduling between parties in the supply chain
Kuo <i>et al.</i> (2010)	Minimize costs and carbon dioxide emissions	Bi-objective model: Pareto-based multi-objective algorithms	Building warehouses in surplus states or districts will help farmers travel shorter distances, creating fewer emissions and saving money on fuel and carbon taxes.
Validi (2014)	Optimize total costs, CO2 emissions, and vehicle routes	Multi-objective model; Solutions approached by MOPSO optimizer and DoE; Results ranked by TOPSIS	
Lee <i>et al.</i> (2006)	Optimize the routing schedule; Minimize transportation and vehicle costs	Mathematical model; Tabu search algorithm	Near-optimal solutions that have the average percentage error of less than 4% in a reasonable amount of time
Yu <i>et al.</i> (2012)	Minimize cost and schedule violation; Maximize quality	Modified FMOP model; Soft time-window mechanism	A tight time window with high penalties is recommended to manage uncertainty in the supply chain, especially in a lean supply chain.
Spliet and Gabor (2014)	Minimize transportation costs	Branch-price-and-cut algorithm	A decrease of 5.42% in transportation costs.
Phan and Kim (2015)	Smoothing the peaks in truck arrivals at the port	Distributed and centralized decision-making model.	For large-scale problems, solutions are generated faster by DDM than by CDM
This Study	Minimize costs related to transportation and violations of delivery quantity and time	Propose an optimal model for the delivery plan, considering time, route, and quantity	Provides a detailed, specific plan for delivery routes, times, and quantities

Table 2 serves as a comprehensive tool for summarizing relevant papers, offering a condensed overview of their key elements, including the purpose, methods employed, and findings. This structured table is instrumental in distilling and organizing the essential information gleaned from diverse articles, providing a systematic means to synthesize and comprehend the contents of the related literature. By encapsulating the purpose, methods, and findings in a concise format, Table 2 facilitates a streamlined approach to reviewing and analysis, empowering researchers and readers to grasp the nuances of various papers efficiently

and aiding in the synthesis of a comprehensive understanding of the collective knowledge presented in the literature.

Simulated annealing is a widely used metaheuristic algorithm that helps researchers and decision-makers find optimal solutions through local search by employing hill-climbing moves to escape local optima. Its popularity stems from its convergence properties and ease of implementation, making it effective for continuous optimization problems, as noted by Aarts and Lenstra (1997). Mousavi *et al.* (2013) applied traditional simulated annealing and a hybrid method combining simulated annealing and tabu search to solve an

NP-hard problem related to cross-dock center location and vehicle routing scheduling. Their results showed minimal variance (less than 5%) between the two algorithms for datasets with fewer than 50 customers. Wang *et al.* (2017) addressed a vehicle routing problem with split deliveries using a mixed-integer linear formulation, combining two-layer simulated annealing and tabu search, with experiments revealing that while tabu search performed better with medium-sized datasets, simulated annealing excelled in solving larger problems efficiently. Similarly, Vincent *et al.* (2021) introduced a vehicle routing problem featuring multiple cross-docks and heterogeneous vehicle fleets, developing a mixed-integer linear model alongside an adaptive neighborhood simulated annealing algorithm that achieved a 0% gap with the best-known solution, highlighting the algorithm's competitiveness in complex scenarios. This algorithm is also used in the research described.

3. METHODOLOGY

3.1 Problem Statement

This research centers on the intricacies of a cross-dock model employed in the distribution of frozen goods. The central hurdle encountered by this system involves achieving a balance between customer orders and the quantities delivered.

The problem arises due to the loading of pallets with products instead of precisely distributing the requested quantities as specified by customers, which is especially significant in the context of seafood distribution. Distinct product categories are available in diverse packaging formats such as bags, foam boxes, or cartons, each possessing distinct weight attributes. In order to maintain the quality and freshness of the products, the cross-dock warehouse strictly disallows any modifications to the initial packaging. In this operational approach, the primary role of the cross-dock warehouse is to ensure that products are matched with customer requirements prior to delivery, focusing on optimizing distribution efficiency rather than repackaging. This ensures that customers receive products in the exact packaging as provided by suppliers. However, due to this approach, discrepancies between ordered and delivered quantities may occur, which must be anticipated and managed effectively.

It is important to note that delivering more than customer demand is acceptable in this context. Customers utilizing cross-dock services frequently encounter varying and unforeseeable daily seafood demand. Consequently, order quantities are determined based on the average demand calculated from past data. If the cross-dock delivers more than requested, customers can store the surplus in their freezer facilities. Similarly, delivering less than the ordered amount is also acceptable, but the quantities must fall within an agreed range. The upper limit of this range is determined by the customer's freezer capacity, while the lower limit is set by their safety stock requirements. The cross-dock system is structured around a collaborative relationship between adaptable supply and flexible demand. Prior to commencing their collaboration, the cross-dock facility and its customers establish a mutual understanding of this arrangement, formalizing it within their contractual agreement.

With a focus on effectiveness and meeting customer expectations, the system meticulously evaluates each order in comparison to the customer's prior requests. This guarantees that the quantities delivered closely align with expectations, minimizing discrepancies and enhancing overall customer satisfaction. To further streamline distribution and cut shipping costs, the system combines orders strategically, grouping them by delivery schedules and customer locations. Nevertheless, in the pursuit of cost-effectiveness and operational efficiency, there may be circumstances where it is not feasible to strictly adhere to customer delivery preferences. To maintain service quality, the system is prepared to accept fines when deliveries fall short of expectations, ensuring that service levels are upheld.

3.2 Assumption

Key assumptions are essential for defining and simplifying the logistics problem in the mathematical model being used. First, it assumes delivery trucks have a maximum operational time and do not return to their starting points, reflecting real-world one-way delivery scenarios. Another assumption in constructing the mathematical model is that loading and unloading times are consistent across all customer locations. While actual loading and unloading durations can vary due to factors like product type and equipment efficiency, this assumption helps maintain clarity and simplicity in the model.

A fixed interval between deliveries is a key parameter in the logistics model, establishing a clear temporal framework. This consistency simplifies route optimization and enables systematic planning and execution of deliveries. The model assumes that consumer demand and delivery schedules are predetermined and well understood. Each customer has a defined delivery time window, which further streamlines the scheduling process. This structured approach optimizes the delivery process and improves efficiency in meeting customer needs and expectations within the specified time constraints.

To manage fluctuations in supplied product quantities, the model assumes that variations must stay within an acceptable range defined by the customer. This limit ensures deviations remain manageable, preventing both overdelivery and underdelivery. By establishing these predefined ranges, the model aims to balance customer expectations with operational efficiency, providing a structured approach to managing quantity variations within realistic constraints.

3.3 Proposed Model

The mathematical model will be presented after clarifying some aspects in order to clearly define the problem:

- **Inputs:** The parameters are categorized into those related to the cross-dock and the customer. The cross-dock parameters include details about available vehicles and products. On the customer side, inputs consist of demand requirements and preferred delivery time windows, along with the allowable deviations for demand and delivery time windows.
- **Outputs:** The output identifies which vehicles will be used and maps each customer to their respective delivery vehicle. Additionally, it outlines the quantity of goods to be delivered and the delivery time for each customer.

- Objectives: The objectives include minimizing penalties for late or early deliveries and incorrect quantities, while also optimizing vehicle usage fees. The overall goal is to reduce operational costs and maintain high service quality.

The proposed model is based on the development and expansion of the Tran *et al.* (2024) basic model, with the incorporation of delivery quantity, time appointment, and scheduling elements. Prior to establishing the objective functions and constraints for the model, a comprehensive overview of the pertinent notations, parameters, and decision variables was presented.

Notations

- i, j, h : Customer index
- k : Truck index
- p : Product index

Input parameters

- $C = \{0, 1, 2, \dots, n\}$: The number of customers that the company must serve
- $P = \{1, 2, \dots, p\}$: The number of product types that the company will provide
- $K = \{1, 2, \dots, k\}$: The number of vehicles the company has available for delivery
- F_k : Fixed cost when using truck k
- c_{ij} : Cost when moving from customer i to customer j
- g_{ij} : Time interval when moving from customer i to customer j
- C_k : Capacity of truck k
- q_{ik} : Most preferable time interval at which truck k arrives at customer i
- w_{ik}^- : Cost of early arrival by a unit time compared with the preferable time interval customer i by truck k
- w_{ik}^+ : Cost of late arrival by a unit time compared with the preferable time interval customer i by truck k
- b_i^l : Earliest possible (lower) bound of time window for customer i
- b_i^u : Latest possible (upper) bound of time window for customer i
- H_p : Amount of product p at cross-dock
- D_{pi} : Amount of product p customer i required
- U_{pi} : Highest amount of product p can be received by customer i
- L_{pi} : Lowest amount of product p can be received by customer i
- Ce_{pi} : Unit penalty cost initiated if amount of product p between U_{pi} and k_{pi}^u
- Cl_{pi} : Unit penalty cost initiated if amount of product p between L_{pi} and k_{pi}^l
- k_{pi}^u : Upper bound for highest amount of product p can be received by customer i
- k_{pi}^l : Lower bound for lowest amount of product p can be received by customer i

Decision variables

- (Bin) Y_{ijk} : Truck k move from customer i to j
- (Bin) Z_k : Truck k being used
- (Real) Q_{pik} : Amount of product p to customer i by truck k
- (Integer) X_{ik} : Time interval that truck k delivery to customer i

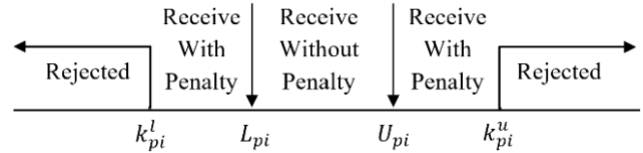


Figure 2 Graphic of delivery quantity parameters.

Incorporating these definitions, the objective function and the set of constraints are subsequently represented by the following model. In contrast to the model proposed by Tran *et al.* (2024), this model incorporates modifications to constraints (8), (9), and (10) to limit consecutive deliveries between customers, ensuring that each customer is served by a single truck.

Minimize

$$\sum_k (F_k Z_k + \sum_i \sum_j c_{ij} Y_{ijk}) \quad (1)$$

$$+ \sum_k \sum_i [w_{ik}^- (q_{ik} - X_{ik})^+ + w_{ik}^+ (X_{ik} - q_{ik})^+] \quad (2)$$

$$+ \sum_p \sum_i \sum_k [Ce_{pi} (Q_{pik} - U_{pi})^+ + Cl_{pi} (L_{pi} - Q_{pik})^+] \quad (3)$$

Subject to:

$$b_i^l \sum_j Y_{ijk} \leq X_{ik} \leq b_i^u \sum_j Y_{ijk}, \forall k, i \quad (4)$$

$$k_{pi}^l \leq \sum_k Q_{pik} \leq k_{pi}^u, \forall p, i \quad (5)$$

$$\sum_i \sum_p Q_{pik} \leq Z_k C_k, \forall k \quad (6)$$

$$\sum_i \sum_k Q_{pik} = H_p, \forall p \quad (7)$$

$$X_{ik} + g_{ij} - M(1 - Y_{ijk}) \leq X_{jk}, \forall i, j, k \quad (8)$$

$$\sum_k \sum_i Y_{ijk} = 1, \forall j \quad (9)$$

$$\sum_k \sum_j Y_{ijk} = 1, \forall i \quad (10)$$

$$\sum_j Y_{0jk} = Z_k, \forall k \quad (11)$$

$$Q_{p0k} = 0, \forall p, k \quad (12)$$

$$Y_{ijk} \leq Z_k, \forall i, j, k \quad (13)$$

$$Q_{pik}, X_{ik} \geq 0, \forall p, i, k \quad (14)$$

The objective functions (1), (2), and (3) are employed to encapsulate the goals pursued by the problem: minimizing the cost associated with truck utilization, mitigating the penalty cost of late or early arrivals, and addressing the penalty cost associated with delivering below or exceeding customer demand.

The model introduced in this paper incorporates a diverse set of constraints to enhance the seamless execution of distribution and transportation operations. Specifically, constraints (4) and (5) are established to ensure that the delivery time and product quantity fall within the acceptable range, as defined by the lower and upper limits. Simultaneously, constraint (6) plays a crucial role in ensuring that the trucks do not exceed their assigned capacities, thereby optimizing the allocation of loads.

Progressing further, constraints (7) establish a crucial relationship between the combined product quantity for all customers and the quantity received from the supplier via the cross-dock, thereby achieving a balance between demand and supply. Additionally, constraints (8) stipulate that the completion time for serving customer i must be less than or equal to the initiation time for serving customer j .

Subsequently, constraints (9) and (10) indicate that each customer can exclusively be supplied by one truck, a vital parameter for efficient routing. Constraints (11) and (12) indicate that point $i = 0$ is the starting point; hence, the quantity of the product here is set to 0. Constraint (13) ensures that vehicles used for transport from customer i to customer j must have been previously allocated. Constraint (14) represents that the decision variables Q_{pik} and X_{ik} must

be larger than or equal to 0. Collectively, these constraints form a resilient mathematical model that serves as the foundation for optimizing transportation and distribution planning, particularly with regard to minimizing operating costs.

After establishing the model, a thorough evaluation will be conducted using sample problems and various methods, including trial-and-error and the CPLEX optimization tool. This evaluation aims to test the model's robustness and efficiency under different scenarios. Following this, strategic algorithms will be integrated to further refine and enhance the solution. This iterative process of evaluation and refinement highlights the commitment to achieving a strong and optimal solution for the complexities of distribution.

3.4 Model Validation

3.4.1 Solving by Trial-and-Error Method

To validate the model, a trial-and-error approach is utilized. The dataset employed for this method consists of two trucks, three customers, and two product types. The logistics operations are constrained by a narrow 4-hour time window, spanning from 6:00 A.M. to 10:00 A.M., which is further divided into 48 five-minute time slots. These stringent temporal constraints make resource allocation and scheduling critical for optimizing operations and adhering to the strict time limits. Effectively managing these factors is crucial for navigating the intricacies of the scenario.

Further information about this trial-and-error calculation method can be found in the paper written by Tran

et al. (2024). The method involves the generation and assessment of all potential scenarios to identify the optimal one. Each objective is addressed separately to streamline the process. The scenarios are listed, their costs are combined, and those that do not meet the requirements are eliminated. The remaining scenarios are thoroughly analyzed to select the most favorable option. This approach extensively explores potential solutions and enhances the decision-making process.

After a thorough analysis of the aforementioned findings, it becomes clear that scenario 1 stands out as the most favorable option, as visually illustrated in **Fig. 3**. In this particular scenario, Truck 1 is strategically assigned to allocate customers in the order of 1 - 2 - 3. Delving into the intricacies of scheduling, it is revealed that a specific time window, denoted as $t = 5$ and spanning from 6:20 A.M. to 6:25 A.M., is allocated for the completion of the delivery involving 47 kg of Product 2 to Customer 1. As a result, the carefully devised schedule designates time window $t = 11$, referring to 6:50 A.M. to 6:55 A.M., for the delivery of 72 kg of Product 1 to Customer 2. Lastly, the delivery of 83 kg of Product 1 to Customer 3 is scheduled for time window $t = 20$, aligning with 8:05 A.M. to 8:10 A.M. These meticulous sequence prioritizations and time allocations underscore the effectiveness of scenario 1 in ensuring not only the efficiency but also the punctuality of product deliveries, all while adhering to the predetermined constraints.

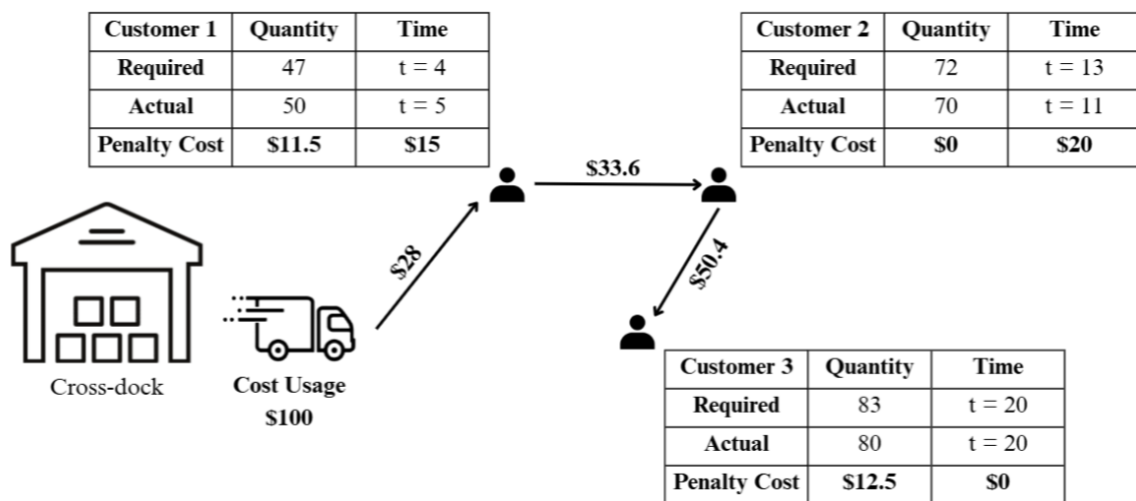


Figure 3 Scenario 1 indicates as the most favorable option.

Nevertheless, the trial-and-error method often entails lengthy execution times and may not yield high accuracy, particularly when dealing with larger datasets. As a result, employing the CPLEX method becomes necessary to effectively solve more substantial problems within a reasonable timeframe.

3.4.2 Solving by CPLEX

The program is executed in Jupyter Notebook using the CPLEX and NumPy modules. It is run on a Dell 7440 laptop with 8.00 GB of RAM, a 64-bit operating system, and an x64 processor running Windows 10 Pro version 22H2.

Furthermore, after model validation was conducted in Jupyter Notebook, the model was further tested using IBM ILOG CPLEX Optimization Studio. Within a period of 1.21

seconds, the model produced comparable results and featured a more user-friendly and easy-to-follow interface for results, similar to Table 3.

Table 3 CPLEX’s results.

Decision Variables	Results	Total Cost
Y_{0-1-1}	1.0	271.0
Y_{1-2-1}	1.0	
Y_{2-3-1}	1.0	
Z_1	1.0	
Q_{1-2-1}	72.0	
Q_{1-3-1}	83.0	
Q_{2-1-1}	47.0	
X_{1-1}	5.0	
X_{2-1}	11.0	
X_{3-1}	20.0	

Thus, the model has been executed on CPLEX, yielding the same trial-and-error results depicted in Table 4, confirming the validation of the model.

Table 4 Comparison between Trial-and-Error and CPLEX.

	Trial-and-Error	CPLEX
Objective Value	271.0	271.0
Time Requirement	3 hours +	1.21 second
Difference	00.0%	00.0%

3.5 Simulated Annealing Algorithm

According to the above results, it is evident that CPLEX struggles to solve big data problems within a reasonable timeframe. Therefore, a tailored algorithm will be considered an alternative approach to enhance computational efficiency and address the limitations observed with CPLEX.

Simulated annealing has demonstrated strong potential in addressing complex transportation optimization challenges. Oudani (2021) applied simulated annealing to optimize the location of intermodal terminals in the freight terminal location problem, a domain still in its early research stages. The proposed mixed integer model, combined with an efficient simulated annealing algorithm, not only provided optimal solutions for small instances using the CPLEX 12.10 solver but also outperformed CPLEX in both objective cost and processing time for larger datasets. Similarly, Vincent *et al.* (2021) developed a simulated annealing algorithm to

tackle a new variant of the vehicle routing problem with time windows and the vehicle routing problem with partial loads. Their approach achieved near-optimal results for small datasets of the vehicle routing problem with time windows and outperformed the Gurobi solver in instances of the vehicle routing problem with partial loads, demonstrating simulated annealing’s adaptability to different problem scales. Additionally, Yu *et al.* (2016) introduced a simulated annealing-based adaptive neighborhood algorithm for solving the vehicle routing problem with multiple cross-docks and a heterogeneous fleet of vehicles. The algorithm proved highly competitive, achieving a 0% gap with the best-known solution. These studies collectively indicate that simulated annealing is not only versatile across various transportation scenarios but also offers robust performance in solving complex and large-scale optimization problems.

3.5.1 Initial Solution

In this study, the simulated annealing algorithm begins with an initial solution that satisfies vehicle capacity constraints and meets the arrival times for each customer.

- **Step 1:** Vehicles are organized based on their capacity, ranging from the smallest to the largest. Meanwhile, customers are arranged according to their delivery times, starting with the earliest and ending with the latest.
- **Step 2:** In the same order as mentioned earlier, choose the vehicles one by one to assign to customers. Each time a customer is assigned, ensure that both basic constraints mentioned previously are satisfied.
- **Step 3:** Determine whether the quantity of products received from suppliers is in excess of or short of the quantity ordered.
- **Step 4:** Sort the guests in ascending order of penalty cost.
- **Step 5:** Distribute the excess or shortage quantity depending on the case.
- **Step 6:** Calculate the objective function.

The example below illustrates how to generate an initial solution. Data from the sample problem will be used to visualize and simplify the process (Figure 4).

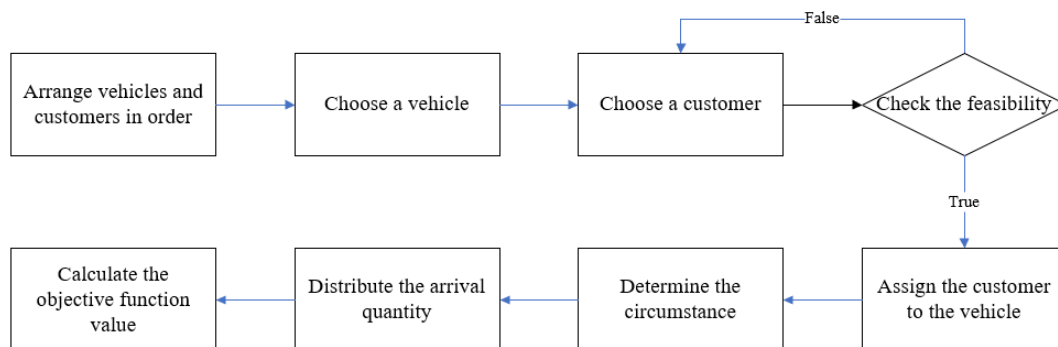


Figure 4 Process of generating initial solution.

3.5.2 Neighborhood Search Mechanisms

This study uses the Simulated Annealing algorithm, which incorporates three neighborhood search mechanisms—swap, reversion, and insertion—to identify better customer combinations for vehicles. Each mechanism has an equal chance of being chosen to generate a new solution. Below is a description of these mechanisms.

- **Swap:** Two customers with the same delivery order between the two vehicles are randomly chosen, and their positions are exchanged to obtain a new solution.
- **Reversion:** A vehicle within the solution will be selected randomly, and the customers in the chosen vehicle will be sorted in reverse order.

- **Insertion:** If the two vehicles are not initially next to each other, a customer from one of them will be chosen randomly. The customer selected using this method will then be inserted into the other vehicle while maintaining their original order from the previous vehicle.

3.5.3 Simulated Annealing Method

In this research, the simulated annealing algorithm is conducted using initial temperature (T_0), final temperature (T_f), and temperature reduction rate (alpha). The algorithm begins by setting the current temperature (T) to the initial temperature. After each iteration, the current temperature (T) is reduced in proportion to alpha. The algorithm stops when the current temperature falls below the final temperature. If the new solution doesn't offer a better cost than the current best solution, it will be accepted based on a probability calculated from the current temperature, as well as the costs of the new and current best solutions

The specific steps are outlined below:

- **Step 1:** Set T_0 , T_f and alpha
- **Step 2:** Create the initial solution following the steps outlined in 3.5.1
- **Step 3:** The objective function of the initial solution is calculated and updated to become the best solution (A)
- **Step 4:** Set the current temperature T as the initial temperature T_0

- **Step 5:** Simulated Annealing algorithm

To conduct runs on large-scale problems, the initial temperature, final temperature, and temperature reduction rate should all be chosen according to the desired number of iterations. To achieve 200 iterations, a set of $T_0 = 100$, $T_f = 15$, and alpha = 0.9905 is recommended.

After establishing the Simulated Annealing Algorithm application method, a program is developed in Python to solve sample data and other large datasets. The program is run on Jupyter Notebook using Python 3.10. The programming process takes place on a Dell 7440 laptop with 8.00 GB of RAM, a 64-bit operating system, and an x64 processor running Windows 10 Pro version 22H2. The solution obtained after running the Simulated Annealing algorithm is similar to the one obtained by the manual method in the previous part.

4. EVALUATION OF SOLUTION EFFECTIVENESS

Table 5 shows the test data set, including subsets S3, S5, S7, ... S35 randomly selected. The evaluation will assess the solution's accuracy by checking constraint satisfaction, recommendations, and overall solution quality. As planned, the distribution problem will be optimized by the CPLEX program, which will receive 17 sets of data.

Table 5 Test results statistics of CPLEX program.

Data Set	Customer	Truck	Product	Objective Value	Time Requirement
S3	3	2	2	271.0	00.12 min
S5	5	2	2	255.3	06.16 min
S7	7	3	3	539.4	10.18 min
S10a	10	5	5	1467.2	20.42 min
S10b	10	3	4	758.9	18.35 min
S12	12	5	5	874.5	30.12 min
S15a	15	5	5	2076.2	42.48 min
S15b	15	5	7	1018.9	63.06 min
S18	18	6	6	1229.1	95.20 min
S20a	20	8	8	N/A	24 hours +
S20b	20	10	10	N/A	24 hours +
S22	22	10	10	N/A	24 hours +
S25	25	10	15	N/A	24 hours +
S27	27	10	15	N/A	24 hours +
S30	30	10	15	N/A	24 hours +
S32	32	10	15	N/A	24 hours +
S35	35	10	12	N/A	24 hours +

After the implementation of the plan to test the combination of the CPLEX program, it was observed that generating solutions took a significant amount of time, and it was not feasible to obtain an optimal solution with large data sets. Therefore, the application of the Simulated Annealing Algorithm is deemed necessary to ascertain the optimal solution for large data sets.

For the Simulated Annealing Algorithm, a corresponding appropriate solution will be generated for each run of the program. To ensure an objective evaluation, 10 runs are conducted for each dataset. The Objective Value results of Simulated Annealing are the best among these 10 runs and compared with the results obtained from CPLEX. (Table 6).

The results from using the Simulated Annealing Algorithm closely match those obtained from using CPLEX before, especially for datasets S3 and S5. In the case of dataset S18, the results yielded by the Simulated Annealing

Algorithm indicate an acceptable difference from those produced by CPLEX. Notably, for datasets S20 to S35, where CPLEX failed to provide a solution within a 24-hour timeframe, the Simulated Annealing Algorithm swiftly generated results in approximately 1 to 5 minutes. This indicates that the Simulated Annealing Algorithm can deliver solutions that are comparable to the optimal outcomes from CPLEX within a significantly shorter period. Consequently, practical challenges associated with large datasets can be effectively addressed using the Simulated Annealing Algorithm. This highlights how useful the Simulated Annealing Algorithm is for solving real-life problems. It provides a reliable way to find solutions and helps the company make informed decisions.

In summary, the effectiveness of the Simulated Annealing Algorithm is demonstrated by its close matching of the results from CPLEX, especially across different

datasets. Its capacity to quickly produce solutions for datasets larger than what CPLEX can handle highlights its practical usefulness in addressing large-scale issues. Using

the Simulated Annealing Algorithm delivers dependable solutions and enables decision-makers to make well-informed choices.

Table 6 Test results statistics of CPLEX and simulated annealing algorithm.

Data Set	CS	TK	PD	CPLEX		SA		Difference
				OV	TR (min)	OV	TR (min)	
S3	3	2	2	271.0	00.12	271.0	00.02	00.00%
S5	5	2	2	255.3	06.16	264.5	00.07	03.60%
S7	7	3	3	539.4	10.18	557.8	00.12	03.41%
S10a	10	5	5	1467.2	20.42	1484.1	00.18	03.26%
S10b	10	3	4	758.9	18.35	789.3	00.25	04.01%
S12	12	5	5	874.5	30.12	912.9	00.32	04.39%
S15a	15	5	5	2076.2	42.48	2154.7	00.35	03.78%
S15b	15	5	7	1018.9	63.06	1067.4	00.48	04.76%
S18	18	6	6	1229.1	95.20	1287.8	00.52	04.78%
S20a	20	8	8	N/A	N/A	3112.4	01.07	-
S20b	20	10	10	N/A	N/A	1523.5	01.15	-
S22	22	10	10	N/A	N/A	2012.3	01.26	-
S25	25	10	15	N/A	N/A	3247.6	01.37	-
S27	27	10	15	N/A	N/A	1172.9	01.41	-
S30	30	10	15	N/A	N/A	2045.1	02.15	-
S32	32	10	15	N/A	N/A	2835.2	03.39	-
S35	35	10	10	N/A	N/A	3699.7	05.46	-

* Note: CS – Number of Customers; TK – Number of Trucks; PD – Number of Products; TR – Time Requirement; OV – Objective Value

5. CONCLUSION

This project addresses the challenges of frozen product distribution in Ho Chi Minh City, focusing on cross-docking, vehicle allocation, and managing delivery variations. It successfully developed an optimization model for three key costs: transportation, penalties for early and late deliveries, and penalties for over and under quantities. The model was validated using the trial-and-error method and CPLEX, with the Simulated Annealing algorithm applied for larger datasets, providing quicker solutions. This robust model helps minimize costs while ensuring timely deliveries, offering an efficient approach to frozen product distribution in a complex urban environment.

Future enhancements could include developing a multi-day distribution model, allowing for long-term cost forecasting and streamlining planning efforts. A model that enables vehicles to return to pick up additional orders could also optimize vehicle usage and reduce costs. Combining Simulated Annealing with other algorithms could further improve solutions, offering practical benefits to the frozen goods distribution industry by enhancing efficiency and ensuring timely deliveries in dynamic urban settings.

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REFERENCES

Aarts, E. H., Korst, J., & van Laarhoven, P. J. (1997). Local search in combinatorial optimization, Chapter 4, *Simulated Annealing*. John Wiley & Sons Ltd, 30, pp. 91-120.
 Acevedo-Chedid, J., Soto, M. C., Ospina-Mateus, H., Salas-Navarro, K., & Sana, S. S. (2023). An optimization model for routing-location of vehicles with time windows and cross-

docking structures in a sustainable supply chain of perishable foods. *Operations Management Research*, 16(4), pp. 1742-1765.
 Ahkamiraad, A., & Wang, Y. (2018). Capacitated and multiple cross-docked vehicle routing problem with pickup, delivery, and time windows. *Computers & Industrial Engineering*, 119, pp. 76-84.
 Akkerman, F., Lalla-Ruiz, E., Mes, M., & Spitters, T. (2022). Cross-docking: current research versus industry practice and industry 4.0 Adoption. *Smart Industry–Better Management*, pp. 69-104.
 Avishan, F., Yanıkoğlu, İ., & Soysal, M. (2025). Adaptive optimization approach for production and distribution planning of perishable food products under demand uncertainty. *Annals of Operations Research*, pp. 1-48.
 Bavar, F., Sabzehparvar, M., & Rad, M. A. (2023). Enrutamiento verde de vehículos de transporte de objetivos múltiples con cross docks bajo la restricción de ventana de tiempo. *Nexo Revista Científica*, 36(02), pp. 208-225.
 Birim, Ş. (2016). Vehicle routing problem with cross docking: A simulated annealing approach. *Procedia-Social and Behavioral Sciences*, 235, pp. 149-158.
 Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management Science*, 6(1), pp. 80-91.
 Dawande, M., Geismar, H. N., Hall, N. G., & Sriskandarajah, C. (2006). Supply chain scheduling: distribution systems. *Production and Operations Management*, 15(2), pp. 243-261.
 Gmira, M., Gendreau, M., Lodi, A., & Potvin, J. Y. (2021). Tabu search for the time-dependent vehicle routing problem with time windows on a road network. *European Journal of Operational Research*, 288(1), pp. 129-140.
 Goodarzi, A. H., Tavakkoli-Moghaddam, R., & Amini, A. (2020). A new bi-objective vehicle routing-scheduling problem with cross-docking: Mathematical model and algorithms. *Computers & Industrial Engineering*, 149, pp. 106832.
 Gunawan, A., Widjaja, A. T., Vansteenwegen, P., & Vincent, F. Y. (2021). A matheuristic algorithm for the vehicle routing

- problem with cross-docking. *Applied Soft Computing*, 103, pp. 107163.
- Hosseini, S. D., Shirazi, M. A., & Karimi, B. (2014). Cross-docking and milk run logistics in a consolidation network: A hybrid of harmony search and simulated annealing approach. *Journal of Manufacturing Systems*, 33(4), pp. 567-577.
- Jamil, A., Abdallah, B. N., & Leksono, V. A. (2021). Firefly algorithm for multi-type vehicle routing problem. In *Journal of Physics: Conference Series* (Vol. 1726, No. 1, pp. 012006). IOP Publishing.
- Kallehauge, B., Larsen, J., Madsen, O. B., & Solomon, M. M. (2005). *Vehicle Routing Problem with Time Windows*, pp. 67-98. Springer US.
- Kirkpatrick, S., Gelatt Jr, C.D. & Vecchi, M.P. (1983). Optimization by simulated annealing. *Science*, 220(4598), pp. 671-680.
- Kuo, J. C., & Chen, M. C. (2010). Developing an advanced multi-temperature joint distribution system for the food cold chain. *Food Control*, 21(4), pp. 559-566.
- Lee, Y. H., Jung, J. W., & Lee, K. M. (2006). Vehicle routing scheduling for cross-docking in the supply chain. *Computers & Industrial Engineering*, 51(2), pp. 247-256.
- Liu, S., & Zhang, C. (2023). Robust optimization of agriculture products urban distribution path considering demand uncertainty. *Alexandria Engineering Journal*, 66, pp. 155-165.
- Marcoux, N., Riopel, D., & Langevin, A. (2005). Models and methods for facilities layout design from an applicability to real-world perspective. In *Logistics systems: Design and Optimization* (pp. 123-170). Boston, MA: Springer US.
- Mousavi, S. M., & Tavakkoli-Moghaddam, R. (2013). A hybrid simulated annealing algorithm for location and routing scheduling problems with cross-docking in the supply chain. *Journal of Manufacturing Systems*, 32(2), pp. 335-347.
- Mukherjee, T., Sangal, I., Sarkar, B., & Alkadash, T. M. (2022). Mathematical estimation for maximum flow of goods within a cross-dock to reduce inventory. *Math. Biosci. Eng.*, 19(12), pp. 13710-13731.
- Nguyen, V.A., Jiang, J., Ng, K.M. and Teo, K.M. (2016) Satisficing measure approach for vehicle routing problem with time windows under uncertainty. *European Journal of Operational Research*, 248(2), pp.404-414.
- Oudani, M. (2021). A simulated annealing algorithm for intermodal transportation on incomplete networks. *Applied Sciences*, 11(10), pp. 4467.
- Phan, M.H. & Kim, K.H. (2015). Negotiating truck arrival times among trucking companies and a container terminal. *Transportation Research Part E: Logistics and Transportation Review*, 75, pp. 132-144.
- Rahimi, M., Baboli, A. and Rekik, Y. (2014). A bi-objective inventory routing problem by considering customer satisfaction level in context of perishable product. In *2014 IEEE Symposium on Computational Intelligence in Production and Logistics Systems (CIPLS)* (pp. 91-97). IEEE.
- Spliet, R., & Gabor, A. F. (2015). The time window assignment vehicle routing problem. *Transportation Science*, 49(4), pp. 721-731.
- Theophilus, O., Dulebenets, M. A., Pasha, J., Abioye, O. F., & Kavooosi, M. (2019). Truck scheduling at cross-docking terminals: A follow-up state-of-the-art review. *Sustainability*, 11(19), pp. 5245.
- Tran, H.P., Vu, M.P. & Phan, M.H. (2024). Distribution decision model for cross-docking. *EAI International Conference on Renewable Energy and Sustainable Manufacturing*, Springer Nature, pp. 187-203.
- Van Belle, J., Valckenaers, P., & Cattrysse, D. (2012). Cross-docking: State of the art. *Omega*, 40(6), pp. 827-846.
- Vincent, F. Y., Jewpanya, P., Redi, A. P., & Tsao, Y. C. (2021). Adaptive neighborhood simulated annealing for the heterogeneous fleet vehicle routing problem with multiple cross-docks. *Computers & Operations Research*, 129, pp. 105205.
- Vincent, F. Y., Anh, P. T., Gunawan, A., & Han, H. (2024). A simulated annealing with variable neighborhood descent approach for the heterogeneous fleet vehicle routing problem with multiple forward/reverse cross-docks. *Expert Systems with Applications*, 237, pp. 121631.
- Wang, J., Jagannathan, A. K. R., Zuo, X., & Murray, C. C. (2017). Two-layer simulated annealing and tabu search heuristics for a vehicle routing problem with cross docks and split deliveries. *Computers & Industrial Engineering*, 112, pp. 84-98.
- Wang, Y., Li, Q., Guan, X., Fan, J., Xu, M., & Wang, H. (2021). Collaborative multi-depot pickup and delivery vehicle routing problem with split loads and time windows. *Knowledge-Based Systems*, 231, pp. 107412.
- Xi, X., Changchun, L., Yuan, W., & Hay, L. L. (2020). Two-stage conflict robust optimization models for cross-dock truck scheduling problem under uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, 144, pp. 102123.
- Ye, Y., Li, J., Li, K., & Fu, H. (2018). Cross-docking truck scheduling with product unloading/loading constraints based on an improved particle swarm optimisation algorithm. *International Journal of Production Research*, 56(16), pp. 5365-5385.
- Yesodha, R., & Amudha, T. (2022). A bio-inspired approach: firefly algorithm for multi-depot vehicle routing problem with time windows. *Computer Communications*, 190, pp. 48-56.
- Yu, M. C., Goh, M., & Lin, H. C. (2012). Fuzzy multi-objective vendor selection under lean procurement. *European Journal of Operational Research*, 219(2), pp. 305-311.
- Yu, V. F., Jewpanya, P., & Kachitvichyanukul, V. (2016). Particle swarm optimization for the multi-period cross-docking distribution problem with time windows. *International Journal of Production Research*, 54(2), pp. 509-525.