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The Cost and Time Objectives Minimization in Cross-Dock Truck Scheduling of Perishable Goods Considering Uncertainty

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ABSTRACT

This study optimizes truck scheduling for transporting perishable products considering demand uncertainty. The supply chain of perishable goods is complex due to the critical importance of quality to consumers and presents significant logistical distribution challenges that must be managed effectively. The approach proposed here uses cross-docking, a popular strategy that reduces inventory levels and shortens delivery times. We develop a non-deterministic bi-objective mathematical programming model to minimize cost and time objectives. Minimizing product quality degradation is implicitly included in the cost-related objective function. The model also considers the uncertainty. Also, in the proposed model, which is defined in a multi-period environment, the types of trucks and the loading and unloading times required for each type of product are specified. Considering these parameters together distinguishes this model from existing cross-docking models. For small-sized problems, CPLEX Optimizer provides accurate solutions. For large problems, NSGA-II is used. Comparing CPLEX and NSGA-II on small problems shows no significant performance difference. CPLEX is superior in exact solutions, while NSGA-II is better at considering different alternatives in multi-objective scenarios, showing how they complement each other in optimization. Input parameters are optimized using the Taguchi method to evaluate their impact on NSGA-II. Sensitivity analysis showed that key parameters significantly affect delay and cost, contributing to 22-25% and 12-15% variations, respectively. It is worth noting that increasing product variety has the most significant impact on the total delay weight. Overall, this model increases service flexibility, reduces wasted time, improves customer satisfaction and service level, and ultimately increases profitability.

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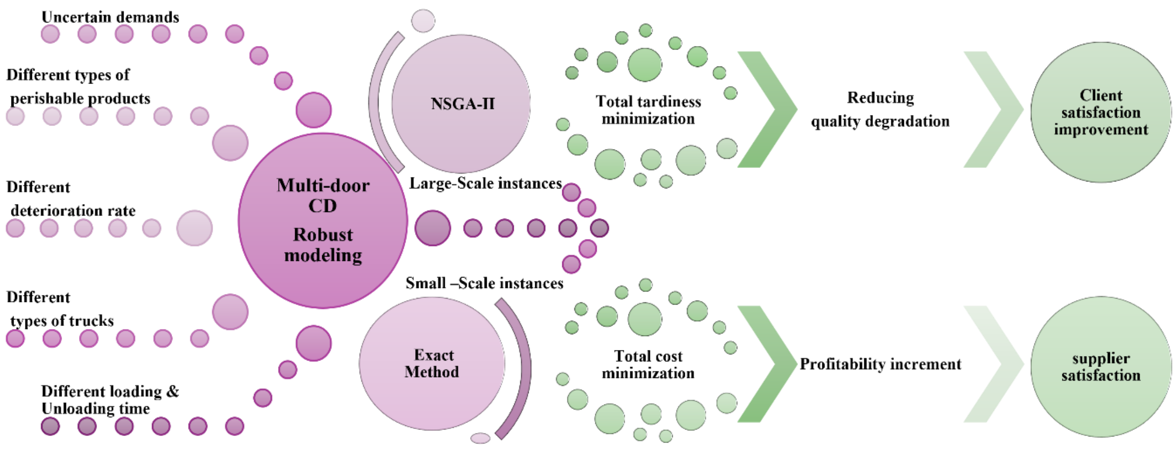
Graphical Abstract



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1. INTRODUCTION

Cross-docking (CD) is a logistics method that transfers goods from one carrier to another without using a warehouse. CD seeks to remove the need for inventory maintenance in traditional warehouses by categorizing goods based on demand patterns and delivery vehicles (1). CD facility temporarily merges goods before distributing them to customers based on destination. The CD is a logistics method enabling direct product distribution from inbound to outbound shipments with little or no storage. It offers warehouse management services if needed. It ensures transportation and better coordination between supply and demand. The management of distribution networks, including cross warehouses, is known as transit warehouses. It is essential in the supply chain (SC) because of its impact on cost reduction and distribution time. Cross-warehousing revolutionizes logistics by drastically reducing processing times and enhancing supply chain efficiency, all while boosting customer and supplier satisfaction (2). Countries worldwide are adopting this system to optimize shipping and performance.

A suitable schedule for the input and output Trucks is essential, specifying which of the incoming Trucks should be unloaded first, which outgoing Trucks should be loaded first, and how the Truck arrangement should be to minimize time and costs. This schedule should specify the order in which incoming trucks are unloaded, the priority of loading outgoing trucks, and their optimal arrangement (3). Transportation, storage, and inventory costs determine the total cost of the SC. Despite the effectiveness of cross-warehousing in reducing costs and time, this issue has been addressed less for perishable goods, especially in an uncertain environment (4).

Perishable products gradually have a limited shelf life but do not spoil immediately. Bakery items (bread and pastries), fresh produce (fruits and vegetables), pharmaceuticals, cut flowers, and others are some examples across various industries.

Because of their vulnerability to contamination from diseases and damage from unpredictable weather, it is challenging to ensure quality standards and product availability. The uncertainty of demand, high rate of deterioration, and short and variable shelf life requiring special storage conditions to reduce the speed of deterioration make managing the perishable products' SC complex. Long-term storage of perishable products without proper storage facilities can adversely affect their quality, safety, and consumption. Spoiled products are usually turned into waste with environmental consequences and high costs (4). Because of the inherent quality degradation associated with perishable products, CD issues cause distinctly different conditions compared to standard storage practices (4).

The real-world scenarios of CD problems could diverge from the findings and insights presented in related research. Ignoring the type of products and focusing on one kind of product may limit the relevant research. In addition, each type of product may have a specific spoilage rate. This loss of quality can lead to cross-docking costs, and it is natural for cross-docking to bear these costs. However, there is an ambiguity in the discussion of perishable products in CD. In this study, the multi-product mode is discussed. Also, product degradation is considered. The classification of Uncertainty in demand for perishable products emerges as a notable and distinct category.

Most existing research primarily focuses on uncertain arrival and loading times (5). This study takes into account the uncertainty of demand. Dealing with uncertainty is important because it directly affects the deterioration of perishable products and can lead to product loss. Demand uncertainty leads to an increase in product spoilage probability. These uncertain conditions lead to uncertainty in truck allocation. The uncertainty complicates the optimal allocation of trucks and potentially leads to increased delays and associated costs. Therefore, accurate truck scheduling is important for perishable goods warehouse managers. This research presents a truck scheduling model for cross-dock warehouses with uncertain demand for perishable products. Due to the products' perishability, a delay penalty can arise. Late delivery can lead to product spoilage, ultimately reducing overall profit and customer satisfaction. This study proposes a dual-objective mathematical model. The proposed model is based on Yu's (6) second basic model but with additional assumptions. The first objective minimizes the weighted sum of tardiness, and the second aims to minimize cross-docking costs, which encompass tardiness fines, transportation and maintenance expenses, and the costs associated with the quality degradation of perishable products. The multi-period assumption for cross-docking facilitates more efficient resource utilization by improving delivery speed. In this context, several products are usually processed simultaneously, which increases the need for precise delivery and careful planning. Given the diverse nature of the products, it is also sensible to account for different loading and unloading times for each one. Considering these variations will lead to fluctuations in loading and unloading times, adding to the complexity of the problem. Based on the above, the following innovations, within the context of some realistic assumptions, are considered, which distinguish this study from previous ones:

- Consideration of multi-period CD.
- Different loading and unloading times for each product.

- Consideration of truck types.
- Consideration of product quality degradation penalty as part of the cost objective.

The assumptions:

- Perishability of products,
- Considering demand uncertainty
- Minimization of cost and time objectives
- Different destruction rates for each product

The organization of the paper is as follows: Section 2 reviews pertinent literature, Section 3 provides an in-depth discussion of the problem and the creation of a non-deterministic two-objective mathematical programming model, Section 4 describes the approach taken to solve the model, Section 5 showcases the results from solving the problem alongside a sensitivity analysis, and Section 6 wraps up with a recap of the study's findings and suggestions for forthcoming research.

2. LITERATURE REVIEW

This paper reviews the related literature based on the model settings, the uncertainty sources and how to deal with them, the considered objective functions, the perishability of the products and their modeling, and finally, the problem modeling and the proposed solution(s). Related articles on truck scheduling in cross-docking are categorized depending on the number of cross-docking doors into single and multi-door (e.g., (7, 8)). To avoid a lengthy review, for a detailed study of truck scheduling at a single-door CD and focus on this paper's topic, refer to Soltani and Sadjadi (7), Forouharfard and Zandieh (9), Arabani et al. (10), Mohtashami (11), Amini and Tavakkoli-Moghaddam (12).

2. 1. The Assumptions In Model Setting

The considered number of doors in the cross-dock, the number of objective functions, products, periods, truck types, the sameness or difference of unloading and loading times for different products, consideration of uncertainty, and consideration of product perishability determine the model settings. Zabihi and Sahraeian (13), Tavana et al. (14), Movassaghi and Avakh Darestani (15), Yaghoubi and Fazli (16), Shahabi-Shahmiri et al. (17), Hashemi-Amiri et al. (18), and Haghgoei et al. (19) considered multi-door CD problem. In contrast, Heidari et al. (20), Essghaier et al. (21), Zheng et al. (22), Theophilus et al. (23), Pan et al. (24), Gallo et al. (25), Nasiri et al. (26), and Fathollahi-Fard et al. (27)considered a single objective function. Also, the above studies considered the uncertainty except for Zabihi and Sahraeian (13), Shahabi-Shahmiri et al. (17) addressed the perishability of the product/products. Shahabi-Shahmiri et al. (17), Hashemi-Amiri et al. (18), and Zheng et al. (22) addressed the multi-product case. Zabihi and Sahraeian (13) introduced a MINLP model to ondptimize the incoming and outgoing truck scheduling. The model handled multiple products with varying capacities and equipment across several temporary storage areas and dock doors within a CD. It simultaneously sequenced perishable products and scheduled trucks to minimize makespan and optimize storage levels. Tavana et al. (14) suggested a bi-objective model to minimize the schedule's costs and delivery time in multi-door CD truck allocation and scheduling issues. They improved transportation efficiency between suppliers and customers by using drones for direct delivery. Sensitivity analysis evaluates model robustness under travel times uncertainty. Movassaghi and Avakh Darestani (15) tackled some cross-docking aspects, including assignment, routing, sequencing, and scheduling of trucks. A proposed MINLP model accounts for uncertainties in truck loading and unloading time, processing time, and resource availability. The model's objective function had fuzzy coefficients to minimize the supply chain's transportation costs. Yaghoubi and Fazli (16) developed a multi-objective, green supply chain cross-docking vehicle routing and scheduling model (VRS) that minimizes total delivery costs and CO_2 emissions, addressing uncertain vehicle emissions using the NSGA-II algorithm. Shahabi-Shahmiri et al. (17) established a novel hybrid methodology for diverse VRP for perishable products in multiple CDs. The approach aims to optimize distribution costs, expedite operational processes, and enhance capacity utilization. Hashemi-Amiri et al. (18) developed a new bi-objective optimization model to manage perishable food supply chains (PFSC). This model handled uncertain demand and created a robust three-layer network. The main goal of this model was to optimize supplier selection, production planning, and distribution routing. This optimization aimed to achieve two main objectives: maximize the reliability of raw material procurement and improve economic efficiency. This model addressed perishable goods' deterioration and customer satisfaction. It used a distributed chance-based approach called DRCC to handle demand uncertainty. This approach provided a more realistic and robust solution to traditional chance-constrained programming. Haghgoei et al. (19) tackled a CD multi-objective truck scheduling problem, minimizing maximum product receipt time, truck emissions, and the assigned-to-door number of trucks, using Fuzzy Logistics to represent product quantities. Heidari et al. (20) proposed two meta-heuristics, NSGA-II and MODE, to solve a multi-door CD problem with time windows for unknown truck arrival times. They aimed to minimize the total cost of the airport operations. Zheng et al. (22) proposed four heuristic algorithms to minimize total operational costs in a mixed-integer linear programming model considering two types of perishable goods in cold-chain multi-door cross-docking and distinct refrigerated and frozen storage areas at varying temperature settings. Theophilus et al. (23) conceived a customized Evolutionary Algorithm for truck scheduling at a cold-chain CD, focusing on minimizing service costs by addressing perishable product degradation. Pan et al. (24) developed a MIP model in which the concept of risk of changes in perishable product deterioration rate in a CD. They utilized a genetic algorithm to schedule trucks. Gallo et al. (25) developed a stochastic MILP model to minimize penalty costs due to uncertain truck arrivals impacting product perishability. They implemented a specialized stochastic genetic algorithm to optimize multi-door cross-docking systems for larger instances. Nasiri et al. (26) tackled demand uncertainty concerning post-distribution (trucks in a cross-dock scheduling problem that lacks storage. A mathematical programming model was proposed to minimize the makespan. The whale meta-heuristic was used to accomplish the proposed model. A flexible multi-door cross-docking facility was analyzed, with time and cost uncertainties modeled as triangular fuzzy numbers in Rajabzadeh and Mousavi (28). Abdoli et al. (29) showed the preference of NSGA-II to MOPSO in obtaining near-optimal Pareto solutions to minimize total completion times and total tardiness in a cross-duck truck scheduling problem under truck breakdown uncertainty. They framed the problem as a bi-objective programming model aimed at minimizing delivery time violations and transportation costs. A hybrid approach using max-min operators and compromise programming addressed the uncertainties. A developed social engineering optimization (SEO) model has been proposed to address a cross-dock truck scheduling problem by Fathollahi-Fard et al. (30). A comparison was conducted between the proposed SEO and a selection of commonly used alternatives. The results showed that the developed SEO achieved higher levels of success in Makespan minimization. Previous valuable studies, including one conducted by Hashemi et al. (18), have considered various assumptions and optimized multiple objective functions, uncertainties, product spoilage, and the gradual decline in product quality. The paper examines similar yet distinct assumptions, focusing on various truck types and a multi-period cross-docking system. The proposed model in this study is based on Yu's (6) second basic model but with additional assumptions, including considering different loading and unloading times based on product type, calculating appropriate truck types tailored to specific product requirements, and others. These assumptions are formulated under demand uncertainty. Table 1 includes the model setting of the most related references in truck scheduling in a multi-door CD.

The following steps are taken to address the identified research gaps:

TABLE 1. Multi-Door Cross-Docking Truck Scheduling References Based On The Assumptions In The Model Settings

Ref.	Obj		Pro		Peri		TrTyp		L/UnL		Un	Pre
	S	M	S	M	S	M	S	M	U	D		
(14)		√	√		√		√		√		√	
(20)	√		√		√		√		√		√	
(26)	√		√		√		√		√		√	
(15)		√	√		√		√		√		√	
(21)	√		√		√		√		√		√	
(28)	√		√		√		√		√		√	
(16)		√	√		√		√		√		√	
(29)		√	√		√		√		√		√	
(25)	√			√	√		√		√		√	
(18)		√		√	√		√	√	√		√	√
(19)		√	√		√		√		√		√	
(30)	√			√	√		√		√			
(27)	√			√	√		√		√			
(13)		√	√		√		√		√			√
(22)	√			√	√		√		√			√
(23)	√		√		√		√		√			√
(17)		√		√	√		√		√			√
(24)	√		√		√		√		√			√
Current Study		√		√		√		√		√	√	√

Obj: Objectives, Peri: Periods,
Pro: Products, Pre: Perishable Product
L: Loading Times Trtyp: Truck-Typ,
UnL: Unloading Times, Un: Uncertainty,
M: Multi, S: Single U: Uniform, D: Different

- A multi-period, multiple-door cross-dock system is used to consider perishable products.
- Under demand uncertainty, a bi-objective MINLP model for scheduling different truck types is developed.
- Different loading and unloading times are based on product type and tailored to specific product requirements.
- The degradation rate of perishable products as a component of cost-related objectives is covered.

2. 2. The Uncertainty Sources and How to Deal with

Uncertainty complicate scheduling problems and necessitate the development of advanced models and algorithms to manage these challenges effectively (25). The uncertainty resources in truck scheduling CD are (Inbound) truck arrival times (20), tuck Breakdown Probability (12), Loading and Unloading Times (31), Demand Uncertainty (18), and others. Uncertainty can impact the overall efficiency and costs. Previous studies addressed strategies for handling uncertainty, such as Dynamic Scheduling (32), Robust Optimization (RO) (33), Predictive-Reactive Rescheduling (26), Time Window (20), Sensitivity Analysis (14), Fuzzy-based Strategies (15), and others. Sensitivity analysis evaluated model robustness under travel times uncertainty in Tavana et al. (14). Heidari et al. (20) employed time windows to handle unknown truck arrival times. Nasiri et al. (26) tackled demand uncertainty concerning post-distribution (Predictive-Reactive Rescheduling) trucks in a cross-dock scheduling problem that lacks storage. Movassaghi et al. handled the uncertainty in costs, demand, and production capacities using fuzzy-interactive multi-objective linear programming. Essghaier et al. (21) employed Fuzzy Chance Constraints to handle the uncertainty of trucks' transfer times. The uncertainty of loading and unloading times, transportation times, and costs of flexible CD doors were tackled through Interval Value fuzzy (IVF) in Rajabzadeh and Mousavi (28). Yaghoubi and Fazli (16) employed fuzzy programming to handle the uncertainty of demand and quantity of CO_2 emissions. Abdoli et al. (29) tackled the truck breakdown uncertainty using probability. Gallo et al. (25) developed a stochastic MILP model to minimize penalty costs due to uncertain truck arrivals impacting product perishability. Hashemi-Amiri et al. (18) handled uncertain demand and created a robust three-layer network using chance constraint programming. Haqhgoei et al. (19) handled the loading and unloading time using fuzzy logic. This study handles the demand uncertainty through a robust optimization model. Altaf et al. {Altaf, 2025 #31considered uncertainties in the parameters of costs and delay and proposed a robust optimization model to handle worst-case scenarios.

Table 2 summarises the sources of uncertainty and how they are dealt with in the most relevant previous papers. Robust optimization minimizes penalties, ensures resource utilization, effectively balances multiple objectives, and is highly scalable {Altaf, 2025 #31} . The RO model ensures that solutions remain feasible despite uncertainties (33). Post-distribution strategies are reactive but have high operational costs. In dynamic scheduling, adjustments rely on accurate real-time data. It is effective if real-time data is accurate, but it may struggle with large-scale systems.

TABLE 2. The uncertainty sources and how to deal with

Ref.	Uncertainty Source	Uncertainty Modelling
(14)	Travel times	Sensitivity analysis
(20)	Truck arrival times	Time window
(26)	Inbound truck arrival times	Predictive-reactive rescheduling
(15)	costs, demand, and production capacities	Fuzzy-interactive multi-objective LP
(21)	Transfer times	Fuzzy chance constraints
(28)	Loading and unloading Transportation times Costs of flexible doors	Interval value fuzzy (IVF)
(16)	Quantity of CO2 Emissions, Demand	Fuzzy Programming
(29)	Truck breakdown	Probability (poisson disribution)
(25)	Truck arrivals	Stochastic mixed linear programming
(18)	Demand and Supply	Chance constraint programming
(19)	Loading and unloading	Fuzzy logistic
(33)	Parameters of costs and delay	Robust Optimization
Current study	Demand	Robust Optimization

2. 3. The Considered Objective Function(S)

Based on the reviewed literature, the most common objective function focuses on minimizing costs (Transportation, Penalty, Product Quality degradation, Waste Due to Perishability) (14-20) and ensuring timely delivery (makespan, delay, tardiness, and earliness) (13-15). These objectives are critical due to the products' perishability and the logistical challenges associated with uncertainties. Cost and time-related objectives are discussed in Tavana et al. (14), Movassaghi and Avakh Darestani (15), Shahabi-Shahmiri et al. (17), Haghgoei et al. (19), and Rajabzadeh and Mousavi (28). Tavana et al. (14) suggested a bi-objective model to minimize the schedule's costs and delivery time in multi-door CD truck allocation and scheduling issues. They improved transportation efficiency between suppliers and customers by using drones for direct delivery.

Movassaghi and Avakh Darestani (15) minimized routing costs and total delivery times and tackled cross-docking aspects. These aspects include assignment, routing, sequencing, and truck scheduling. Shahabi-Shahmiri et al. (17) minimized three objectives: total transportation times, total transportation costs, and a penalty for the earliness and tardiness of perishable products. They optimized distribution costs, expedited operational processes, and enhanced capacity utilization. Haghgoei et al. (19) tackled a CD multi-objective truck scheduling problem using fuzzy logistics, minimizing maximum product receipt time, truck emissions, and the assigned-to-door number of trucks. Rajabzadeh and Mousavi (28) framed the problem as a bi-objective programming model to minimize delivery time violations and transportation costs. Other objectives include stability (34), Supplier reliability (18), and quantity-related objectives such as ac CO_2 emissions (16), as well as accumulated deterioration rate variation (24). Shahabi-Shahmiri et al. (17) supported product quality by imposing penalties for failing to deliver perishable products on time. They minimized the penalties for lateness and earliness as a third objective function, along with the time-related and cost-related objectives. Pan et al. (24) formulated the product deterioration rate as an objective. Altaf et al. (32) considered the overall costs, including operational, penalty, and material handling or temporary storage costs.

Table 3 summarises the objectives of the most relevant previous papers. The current study minimizes tardiness and the cost of the schedule. The penalty for product quality degradation is one component of the cost-related objective function.

TABLE 3. The Considered Objective Functions

Ref.	Time-related	Cost-related	Other
(14)	delivery time	Scheduling costs	
(20)		Average total service cost	
(26)	Total tardiness		Stability
(15)	Total arrival times	Total cost	Coordinated composition of the cost and time objectives
(21)		Total cost	
(28)	Outbound truck tardiness	Total system costs	
(16)		Total Costs	CO2 Emissions
(29)	Total Completion Time, Outbound trucks' earliness and tardiness		
(25)		Total penalty cost of earliness and tardiness, cost of secondary deliveries	
(18)		Total cost	Suppliers' Reliability
(19)	Time to receive the products	Emission cost	The number of assigned trucks
(13)	makespan		Direct shipment
(22)		Total operation cost	
(23)		Total cost	
(17)	Total transportation time	Total transportation cost	Penalty for the earliness and tardiness of perishable products
(24)			Accumulated deterioration rate variation
(33)		overall costs	
Current Study	Total tardiness	Total cost	

2. 4. The Preshiablity of the Products And Its Modeling Way

Zabihi and Sahraeian (13) introduced a MINLP model to handle multiple products while considering their perishability but not the deterioration rate. Shahabi-Shahmiri et al. (17) established a MIP model for VRSP to handle multiple products while considering their perishability and not their deterioration rate. An objective function minimizes the earliness and tardiness of perishable products. Hashemi-Amiri et al. (18) developed a MINLP model based on a Distributionally Robust Chance-Constrained approach that addressed the deterioration of perishable products with different decay rates. It Considered the effects of product decay rates and the penalties associated with time windows. Zheng et al. (22) proposed a MILP model that considers two types of perishable goods and distinct refrigerated and frozen storage areas at varying temperature settings but not the products' deterioration rate. Theophilus et al. (23) conceived a mixed-integer mathematical model addressing perishable product degradation. They consider an exponential probability function to account for the decay of the perishable products. Pan et al. (24) developed an MIP model with the risk of perishable product deterioration rate changes. The IoT and sensor systems collect product deterioration data.

Gallo et al. (25) developed a stochastic MILP model to minimize penalty costs due to uncertain truck arrivals impacting product perishability. Altaf et al. (32) proposed a deterministic MIP formulation extended with a robust optimization model. The current study examines various deterioration rates and aligns with Theophilus et al. (23) by using the exponential probability function for the deterioration of perishable products.

Table 4 summarises the perishability of the product(s).

2. 5. Problem Modeling And Proposed Solution

The modeling approaches include MILP (19), fuzzy logic-based frameworks (21), and stochastic optimization (25). Proposed solutions often rely on meta-heuristics like GA and NSGA-II (19), scenario-based analysis,

TABLE 4. Perishability of the product(s)

	NCDR	IDR	DDR	VDR
(13)	√			
(17)	√			
(22)	√			
(25)	√			
(23)			√	
(18)			√	
(24)				√
Current Study			√	
NCDR	Not Considered Deterioration Rate			
IDR	Identical Deterioration Rate			
DDR	Different Deterioration Rates			
VDR	Variable Deterioration Rate			

heuristics (35), hybrid methods (32) and other techniques. These approaches focus on the challenges of perishability, time sensitivity, and unpredictable factors such as demand and truck arrivals. Table 5 summarises problem modeling and proposed solutions of the most relevant previous papers. The current study proposed a Robust optimization model and employed NSGA-II to handle large-scale instances.

TABLE 5. Problem Modeling And Proposed Solution

Ref.	Modeling	Solution method	
(13)	MINLP	Exact methods	CPLEX
(14)	MILP	Exact methods	Multi-Objective Epsilon constraint
(17)	MIP	Exact	Epsilon - constraint augmented for multi-objective problems
(18)	Robust Optimization model reformulated as MILP	Chance-constraint-based approach	Goal Programming
(26)	MILP	Heuristics	A deterministic scheduling model and a periodic predictive-reactive rescheduling approach
(22)	MILP	Heuristic	4 heuristics based on GRASP (Greedy Randomised Adaptive Search Procedure) and TLSP (Tabu List-based Search Procedure),
(20)	MILP	Meta-heuristics	NSGA-II, MODE
(24)	MIP	Meta-heuristics	GA
(23)	MIP	Meta-heuristics	Customized EA-Based
(15)	MILP	Meta-heuristics	GA, AC
(19)	MILP	Meta-heuristics	GA, PSO, NSGA-II, NRGA
(16)	Fuzzy logic	Fuzzy Programming	NSGA-II
(21)	Fuzzy logic	Fuzzy Chance-Constrained Programming	
(28)	Fuzzy logic	Interval-Valued-Fuzzy (IVF)	Incorporates the Max-Min operator and compromise programming concepts
(25)	Stochastic	Stochastic Mixed Linear Programming	Decision Support Tool (DST) alongside Stochastic Genetic Algorithm-Scenario Tree (SGA-ST)
Current Study	MINLP	Meta-heuristics Exact	NSGA-II

2. 5. 1. Exact Solution Methods Zabihi and Sahraeian (13) introduced a MINLP model. They linearized the model and employed the branch and bound method to solve the MILP model. Tavana et al. (14) suggested a bi-objective mixed integer linear programming optimization model. They solved this model using the epsilon-constraint method. Shahabi-Shahmiri et al.(17) proposed a MIP model and exact hybrid approach, AUGMECON2VIKOR, for a heterogeneous vehicle routing and scheduling problem in a multiple CD system. Hashemi-Amiri et al. (18) developed a bi-objective robust optimization model and a distributed chance-constraint-based approach called DRCC as a solution method. They solved it using an exact method called goal Programming. Nasiri et al. (26) proposed a MILP model. The solution method includes a deterministic scheduling model and a periodic predictive-reactive rescheduling approach to manage disruptions. First, a master schedule was created by solving a deterministic cross-dock scheduling model focused on minimizing total tardiness costs. At predetermined rescheduling points, the system was evaluated, and if discrepancies from the expected state were identified, a new schedule was generated.

2. 5. 2. Metaheuristic Solution Methods Heidari et al. (20) proposed two meta-heuristics, NSGA-II and MODE, to solve a bi-objectives, bi-level optimization model for the multi-door CD problem with time windows for unknown truck arrival times. These methods solved the scheduling problem by comparing their efficacy against a random search-based GA from the existing literature.

Zheng et al. (22) proposed four heuristic algorithms to minimize total operational costs in a mixed-integer linear programming model considering two types of perishable goods in cold-chain multi-door cross-docking and distinct refrigerated and frozen storage areas at varying temperature settings. Theophilus et al. (23) conceived a customized Evolutionary Algorithm for truck scheduling at a cold-chain CD, focusing on minimizing service costs by addressing perishable product degradation. Pan et al. (24) developed an MIP model in which the concept of risk of changes in perishable product deterioration rate in a CD. They utilized a genetic algorithm to schedule trucks. Abdoli et al. (29) showed that NSGA-II prefers MOPSO to obtain near-optimal Pareto solutions to minimize total completion times and tardiness in a cross-duck truck scheduling problem under truck breakdown uncertainty. They framed a bi-objective programming model to minimize delivery time violations and transportation costs. A hybrid approach using max-min operators and compromise programming addressed the uncertainties.

2. 5. 3. Fuzzy Solution Approaches Movassaghi and Avakh Darestani (15) proposed the MINLP model. The objective function of the model had fuzzy coefficients. They employed GA and AC to solve the model. Yaghoubi and Fazli (16) developed a mixed integer multi-objective vehicle routing and scheduling model (VRS). The model employed fuzzy parameters later converted to deterministic values through a defuzzification process using techniques such as those proposed. They employed NSGA-II as a solution method. Haghgoei et al. (19) tackled a CD multi-objective truck scheduling problem, minimizing maximum product receipt time, truck emissions, and the assigned-to-door number of trucks, using Fuzzy Logistics to represent product quantities. Essghaier et al. (21) proposed a MILP model. The solution involved an exact method and utilized fuzzy parameters to handle uncertainties in arrival and operational conditions, which can enhance the model's robustness in real-world applications. Rajabzadeh and Mousavi (28) Proposed a bi-objective MILP model with time and cost uncertainties modeled as triangular fuzzy numbers. The solution was a hybrid approach combining the max-min operator and compromise programming.

2. 5. 4. Stochastic Solution Approaches Gallo et al. (25) developed a stochastic MILP model to minimize penalty costs due to uncertain truck arrivals impacting product perishability. The solution method was a tailor-made stochastic genetic algorithm (SGA) implementing a scenario tree (SGA-ST).

This algorithm was developed to optimize penalty costs associated with late deliveries of perishable products. The current research formulated the underlying problem as a robust Mixed Integer Nonlinear Programming (MINLP) model. The study uses an Lp-metric approach for small-scale problem instances, while the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is applied to the larger scales.

3. DESCRIPTION OF THE PROBLEM

Naturally, perishable products lose their quality if stored for a long time. Even though some products spoil directly without losing quality, this study focuses on the gradually deteriorating products. An example of these products includes certain types of bread. Also, the uncertainty of demand is considered. In response to the uncertainty of demand, a robust model is proposed. Demand uncertainty leads to an increase in lateness, which causes product spoilage probability to increase as well. These uncertain conditions lead to uncertainty in Truck allocation, which increases the uncertainty of the model. The uncertainty in the Truck allows for increased complications in determining optimal quantities and assignments, potentially leading to increased lateness and associated costs. Therefore, scheduling trucks precisely is vital for such product warehouse managers. For Truck scheduling, two statuses of input and output Trucks are assumed. The focus is on two main objectives: managing lateness and its associated costs. The first concerns timing, while the second involves costs, including lateness penalties. Lateness, or delays in product shipments, can lead to customer dissatisfaction. Given the perishable nature of these products, penalties for lateness are significant. Late deliveries can result in spoilage and loss, ultimately decreasing overall profitability. This study proposes a bi-objective mathematical model for truck scheduling in cross-docking warehouses. The first objective is to minimize the weighted sum of lateness, and the second aims to minimize cross-warehousing costs, which encompass lateness fines, transportation and maintenance expenses, and the costs associated with the quality degradation of perishable goods. The assumptions of the model are:

1. The demand is uncertain.
2. The model is multi-product.
3. The model is multi-objective.

4. The model is multi-period.
5. Loading and unloading time is different.
6. The rates of product deterioration are different and embedded in the cost objective.

3. MODEL CONSTRUCTION AND SOLUTION METHOD

The model indices, parameters, and variables are:

Indices	Description
i	Entrance Truck, $i = 1,2,\dots I$
j	Output Truck, $j = 1,2,\dots J$
p	The product type, $p = 1,2,\dots P$
k	Warehouse, $k = 1,2,\dots K$
t	Time, $t = 1,2,\dots T$
v	Truck type, $v = 1,2,\dots V$

Parameters	Description
w_{iv}	The weight of importance of the input Truck i of type v
f_{ip}	The number of units of product p that are unloaded from the input Truck i
f_{jp}	The number of units of product p that are loaded on the output Truck j
PU_{pv}	Unloading time of product p from Truck type v
PL_{pv}	Loading time product p on the Truck of type v
l_j	The time of the last move for the outgoing Truck j
TE	The exchange time of the Trucks
dem_p	The definite demand for perishable products p
$\widehat{dem}_p$	The indefinite demand for perishable products p
λ_p	Deterioration rate of product p per hour
pen_{iv}	Penalty for delay of Truck i of type v
TC_{ijpv}	The cost of transporting a unit of product p from Truck i of type v to Truck j of type v
TS	The time of transfer of the product to the output Truck
CQ_{ijpv}	The cost of change in the quality of perishable product p in the transfer from Truck i of type v to Truck j of type v
$W_{kk'}$	Time to transfer products from warehouse k to warehouse k'
Q_{ijpv}^{τ}	Quality of Product p delivered by Truck i of type v to Truck j of type v at time τ
θ_{iv}	The amount of delay of v-type Truck i
C_{iv}	The time to complete the Truck of type v activity
d_{iv}	The moving time of v-type Truck j from the cross-warehouse
a_{iv}	The arrival time of Truck i of type v in the warehouse
M	A big number
Variables	
p_{ijkv}	1, if Truck i of type v overtakes Truck j of type v in the sequence of incoming Trucks in warehouse k, and zero otherwise.
q_{ijkv}	1, if Truck i of type v overtakes Truck j of type v in the sequence of outgoing Trucks in warehouse k and zero otherwise.
y_{ik}	1, if incoming Truck i is assigned to warehouse k and zero otherwise.
z_{jk}	1, if output Truck j is assigned to warehouse k and zero otherwise.
v_{ijv}	1, if the product from input Truck i of type v is assigned to output Truck j of type v and zero otherwise.
X_{ijpv}	The number of units of product type p transferred from Truck i of type v to Truck j of type v

3. 1. Objective Functions and Constraints

Equation 1 seeks to minimize the weighted sum of tardiness.

$$Min\, z1 = \sum_{i=1}^{I} \sum_{v=1}^{V} w_{iv}\theta_{iv} \tag{1}$$

Equation 2 seeks to minimize cross-storage costs; including tardiness penalty, transportation, storage, and reducing the quality of perishable products.

$$\begin{aligned} Min\, z2 = &\sum_{v=1}^{V} \sum_{i=1}^{I} pen_{iv}\, \theta_{iv} + \\ &\sum_{v=1}^{V} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{p=1}^{P} TC_{ijpv} \,.\, X_{ijpv} + \\ &\sum_{v=1}^{V} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{p=1}^{P} CQ_{ijpv} \,.\, \Delta Q_{ijpv} \end{aligned} \tag{2}$$

Constraint 3 calculates the amount of delay for each activity and determines how much each Truck will be delayed.

$$\begin{cases} \theta_{iv} \geq C_{iv} - d_{iv} \quad \forall i = 1,2,\dots I,, v = 1,2,\dots V \\ \quad \theta_{iv} \geq 0 \quad \forall i = 1,2,\dots I,, v = 1,2,\dots V \end{cases} \tag{3}$$

Constraint 4 shows that the departure time of the input Truck i is greater than or equal to the arrival time of the same Truck, plus the unloading time of all products. This constraint ensures that the input Truck moves when all its products are unloaded.

$$\begin{aligned} &d_{iv} \geq a_{iv} + \sum_{p=1}^{P} f_{ip} \,.\, PU_{pv} \\ &\forall i = 1,2,\dots I, \quad v = 1,2,\dots V \end{aligned} \tag{4}$$

Constraint 5 shows that the moving time of the outgoing Truck i is greater than or equal to the arrival time of the same Truck, plus the unloading time of all products loaded into it. This constraint ensures that the input Truck moves when all its products are unloaded.

$$\begin{aligned} &d_{jv} \geq a_{jv} + \sum_{p=1}^{P} f_{jp} \,.\, PL_{pv} \\ &\forall j = 1, \quad 2,\dots J, \quad v = 1,2,\dots V \end{aligned} \tag{5}$$

Constraint 6 shows that the moving time of output Truck j must be smaller or equal to the last moving time of Truck *j* to maintain the logic of the problem.

$$d_{jv} \geq l_j \quad \forall \text{ j} = 1,2,\dots \text{J}, \ \forall v = 1,2,\dots V \tag{6}$$

Constraint 7 shows that the above limitation requires the departure time of the output Truck j to be less than or equal to the last moving time of Truck j. Otherwise, the logic of the problem is questioned.

$$a_{jv} \geq d_{jv} + TE - M * (1 - \textstyle\sum_{k=1}^{K} q_{ijkv}) \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, v = 1,2,\dots V \tag{7}$$

Constraint 8 indicates a valid sequence for output Trucks. When Truck i overtakes Truck *j* in a warehouse, the entry time of Truck *j* is greater than or equal to the moving time of Truck *i* plus the exchange time of Trucks.

$$a_{jv} \geq d_{jv} + TE - M * (1 - \textstyle\sum_{k=1}^{K} p_{ijkv}) \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, v = 1,2,\dots V \tag{8}$$

Constraint 9 guarantees that the output Truck *j* is assigned to the warehouse *k*, where the input Truck *i* is parked, and the input time of the output Truck *j* is greater than or equal to the moving time of the Truck *i* from the warehouse plus the Truck exchange time.

$$a_{jv} \geq a_{iv} + TE - M * (2 - y_{ik} - z_{jk}) \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, v = 1,2,\dots V, \\ k = 1,2,\dots K \tag{9}$$

Constraint 10 shows that if the products are transferred from the input Truck *i* to the output Truck, the arrival time of the output Truck *j* is greater than or equal to the movement time of the input Truck *i*, plus the time to transfer all the products from warehouse *k* to *k′*.

$$a_{jv} + M * \left(3 - v_{ijv} - y_{ik} - z_{jk}\right) \geq d_{iv} + \textstyle\sum_{p=1}^{P} X_{ijpv} * W_{kk'} \tag{10}$$

Constraint 11 shows that if the products are transferred from the input Truck *i* to the output Truck *j*, the output Truck's arrival time is greater than or equal to the time the input Truck departs, plus the time it takes to transfer the products from the input Truck *i* to the output Truck *j*.

$$a_{jv} + M * \left(1 - v_{ijv}\right) \geq d_{iv} + \textstyle\sum_{p=1}^{P} X_{ijpv} * TS \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, v = 1,2,\dots V, \\ k = 1,2,\dots K, k' = ,2,\dots K \tag{11}$$

Constraint 12 ensures that each incoming Truck is assigned to only one warehouse.

$$\textstyle\sum_{k=1}^{K} Y_{ik} = 1 \quad \forall i = 1,2,\dots I \tag{12}$$

Constraint 13 ensures that each outgoing Truck is assigned to only one warehouse.

$$\textstyle\sum_{k=1}^{K} Z_{jk} = 1 \ \forall j = 1,2,\dots J \tag{13}$$

Constraint 14 guarantees that if incoming Truck *i* overtakes incoming Truck *j*, then incoming Truck *j* cannot overtake incoming Truck *i*. That is, only one Truck can surpass another at a time.

$$P_{ijkv} + P_{jikv} \leq 1 \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, \\ k = 1,2,\dots K, v = 1,2,\dots V \tag{14}$$

Constraint 15 guarantees that if the incoming Truck *i* overtakes the outgoing Truck *j*, the outgoing Truck *j* cannot overtake the incoming Truck *i*, and only one truck can overtake the other one at a time.

$$q_{ijkv} + q_{jikv} \leq 1 \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, \\ k = 1,2,\dots K, v = 1,2,\dots V \tag{15}$$

Constraint 16 shows the limitation of one Truck's right of precedence over another. So, only one of the two Trucks assigned to a warehouse is selected to enter the warehouse first.

$$P_{ijkv} + P_{jikv} \geq Y_{ik} + Y_{jk} - 1 \\ \forall i = 1,2,\dots \text{I}, \text{j} = 1,2,\dots \text{J}, \\ k = 1,2,\dots K, v = 1,2,\dots V \tag{16}$$

Constraint 17 indicates that the number of product units p transferred from the input Truck to the output Truck is identical to the number of product units loaded on the output Truck j. It means the load balance of the input and output Trucks.

$$q_{ijkv} + q_{jikv} \geq z_{ik} + z_{jk} - 1 \tag{17}$$

Constraints 18-20 show the relationship between integer and binary variables. They state that if the binary variable has zero, it will not be possible to communicate with it.

$$\textstyle\sum_{p=1}^{P} X_{ijpv} \leq f_{jp} \tag{18}$$

$$\textstyle\sum_{p=1}^{P} X_{ijpv} \geq V_{ijv} \tag{19}$$

$$X_{ijpv} \leq M * V_{ijv} \tag{20}$$

The above constraint estimates the quality of the product's type at time t and shows the limit of the quality variable.

$$Q_{ijpv}^{\tau} = Q_{ijpv}^{0} . e^{-\lambda_{pv} \tau_{ijpv}} \tag{21}$$

Constraint 22 shows the change in the delivered product quality by input Truck *i* to the output Truck *j*. It indicates changes in quality.

$$\Delta Q_{ijpv} = (Q_{ijpv}^{0} - Q_{ijpv}^{\tau}) v_{ijv} \tag{22}$$

Constraint 23 shows that even under demand uncertainty, the number of items and products entering the cross warehouse must fulfill the demand. In this model, Γ is based on the budget. This parameter creates a balance between the model's level of stability and conservatism.

$$\sum_{p}^{P} X_{ijpv} \geq max(\Gamma \& 1) * \widehat{dem}_p * dem_p \quad (23)$$

Constraints 24 to 28 indicate the range of binary variables of the problem.

$$p_{ijkv} \in \{0\&1\} \quad (24)$$

$$q_{ijkv} \in \{0\&1\} \quad (25)$$

$$y_{ik} \in \{0\&1\} \quad (26)$$

$$z_{jk} \in \{0\&1\} \quad (27)$$

$$v_{ijv} \in \{0\&1\} \quad (28)$$

Constraints 29 to 36 indicate the interval of integer variables of the problem.

$$X_{ijpv} \geq 0 \quad (29)$$

$$W_{kk'} \geq 0 \quad (30)$$

$$TS \geq 0 \quad (31)$$

$$Q_{ijpv}^{\tau} \geq 0 \quad (32)$$

$$\theta_{iv} \geq 0 \quad (33)$$

$$C_{iv} \geq 0 \quad (34)$$

$$d_{iv} \geq 0 \quad (35)$$

$$a_{iv} \geq 0 \quad (36)$$

3. 3. The Solution to The Model Classical methodologies and interactive techniques are commonly employed to optimize multi-objective problems. Classical approaches, such as Lp-metric and ε-constraint, encompass decomposition techniques to transform multi-objective problems into single-objective formulations. They require multiple executions per problem, which is inefficient for large-scale problems. In contrast, evolutionary techniques like Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) efficiently find the Pareto front in a single run, making them suitable for larger problems.

The Lp-metric method is proposed for small-sized problems, while NSGA-II is for larger-scale challenges.

3. 3. 1. The Lp-Metric Method The Lp metric method provides a simple means of formulating a unified objective function. The Lp-metric method minimizes the deviation of existing objective functions from an ideal solution. Accordingly, the complete objective function is as follows:

$$\left\{[\sum_{i=1}^{n} w_i((f_i - f_i^*)/f_i^*)^P]^{\frac{1}{P}}\right\} \quad (37)$$

f_i: The amount of objective function i
f_i^* : The amount of ideal objective function i
w_i: Importance coefficient of objective function i
r: Parameter to emphasize the deviations
The min-max reformulation of the LP metric method is detailed in Equations 38-40.

$$Min\ F \quad (38)$$

$$\text{t: } F \geq w_i(f_i - f_i^*)/f_i^* \quad \forall \text{i} = 1,2,..,\text{n} \quad (39)$$

$$\sum_{i=1}^{n} w_i = 1 \quad (40)$$

3. 3. 2. NSGA-II Method The truck scheduling cross-docking problem is NP-hard because the increase in the number of inbound and outbound trucks exponentially increases the computational time. Therefore, an evolutionary algorithm is proposed to solve these problems (36). Genetic Algorithm (GA) was the most used method to solve large-scale single-objective problems related to cross-dock, appearing in 30% of doctoral theses and articles between 2001 and 2018 (35). Other meta-heuristics, such as differential evolutionary (DE), simulated annealing (SA), tabu search (TS), link state (LS), and Particle Swarm Optimization (PSO), also contributed to solving these problems, with 13%, 13%, 10%, 10%, 5%, and 20% utilization, respectively. GA was also frequently used in articles related to cross-dock logistics, appearing in 50% of articles with the keyword "door assignment," 45% with the keyword "truck sequencing," and 33% with the keyword "truck scheduling" (35).

NSGA-II has strong Pareto-front diversity and good convergence. It is well-established for scheduling problems, easy to adapt, and computationally more efficient for large-scale scheduling than SPEA2. Although MOEA/D is suitable for scalable, many-objective problems, it requires precise weight vector tuning and may struggle with constraints (37). Deb et al. (38) introduced NSGA-II, a refinement of GA designed for multi-objective optimization problems. They upgraded GA to a multi-objective format by adding two key operators to a single-objective GA. This change enables the generation of a Pareto Front (a set of optimal). The two operators are:

- An operator that assigns ranks to the members of a population through a recursive sorting method.
- Additionally, an operator that maintains diversity among solutions that share the same rank.

Since its 2002 introduction, various search and optimization problems, including scheduling, applied the widely used NSGA-II algorithm (39). The predominant algorithm employed in multi-objective scheduling since

2014 is NSGA-II, surpassing in frequency of use both Multi-Objective Ant Colony (MOAC) and Multi-Objective Particle Swarm Optimization (MOPSO) (40). Non-dominated ranking genetic algorithm (NRGA) and NSGA-II were employed in multi-objective scheduling truck problems in a cross-docking system by Haghgoei et al. (19). Abdoli et al. (29) showed that NSGA-II prefers MOPSO in obtaining near-optimal Pareto solutions to minimize total completion times and total tardiness in a cross-duck truck scheduling problem under truck breakdown uncertainty.

3. 3. 2. 1. Solution Representation Here chromosomes represent essential elements of the problem, focusing on three key assignments:

1. Allocating cross-docks to input Trucks for unloading products.
2. Designating cross-docks for output Trucks to load products.
3. Assigning cross-docks to coupled Trucks for both unloading and loading. Figure 1 illustrates a chromosome configuration featuring three input Trucks, two cross-docks, four output retailers, and one coupled Truck with varying capacities for five perishable products over two periods. Each chromosome consists of three segments, addressing specific aspects of the solution.

In Part A of Figure 1, each gene illustrates the unloading logistics of products at different warehouses.

In Period 1, Truck 1 unloads Product 1 at Warehouse 1, Truck 2 unloads Product 2 at Warehouse 2, and Truck 3 also unloads Product 1 at Warehouse 1.

In Period 2, the distribution changes: Truck 1 unloads Product 3 at Warehouse 1, Truck 2 delivers Product 5 to Warehouse 2, and Truck 3 unloads Product 4 at Warehouse 2, which demonstrates the roles of each Truck in the unloading process.

	t=1			t=2		
K=1	1	0	1	3	0	0
K=2	0	2	0	0	5	4
	1	2	3	1	2	3

Part A.

	t=1				t=2			
K=1	0	1	0	3	3	0	1	0
K=2	2	0	4	0	0	4	0	5
	1	2	3	4	1	2	3	4

Part B.

	t=1		t=2	
K=1	1	0	0	3
K=2	0	5	4	0
	UL	L	UL	L

Part C.

Figure 1. The solution representation **Part A.** Assign the entrance Truck *i* with the *p*-th product to the cross-warehouse *k*. **Part B.** Assign the output Truck *j* to cross-warehouse *k* to load product *p*. **Part C.** Assign an input-output Truck to cross-warehouse *k* to unload a product and load another one.

In Part B of Figure 1, the following loading operations occur:

First Period:
- Product 2 is loaded into Truck 1 at cross-warehouse 2.
- Product 1 is loaded into Truck 2 at warehouse 1.
- Product 4 is loaded into Truck 3 at warehouse 2.
- Product 3 is loaded into Truck 4 at cross-warehouse 1.

Second Period:
- Truck 1 goes to cross-warehouse 1 to load product 3.
- Truck 2 heads to cross-warehouse 2 to load product 4.
- Truck 3 is sent to warehouse 1 to load product 1.
- Truck 4 is assigned to warehouse 2 to load product 5.

In part C of Figure 1, the inbound-outbound Truck operates over two periods. In the first period, it unloads product 1 at cross-warehouse 1 and loads product 5 from cross-warehouse 2. In the second period, it unloads product 4 at cross-warehouse 2 and loads product 3 from cross-warehouse 1.

3. 3. 2. 2. Crossover and Mutation Operators The effectiveness of the NSGA-II algorithm depends on selecting crossover and mutation operators to discover new solutions and refine existing ones. In this case, the permutation crossover operator is derived from the existing literature (41). Parent selection utilizes a binary tournament method, while an integer random number defines parent segments. The first offspring is formed by combining the first segment of the first parent with the second segment of the second parent, potentially leading to duplicate genes. We resolve this by substituting duplicates in the first offspring with the corresponding genes from the second offspring, enhancing genetic diversity and optimizing the algorithm's performance. The mutation operator is used in GA to improve solutions. A parent is selected via a binary tournament. A random integer from 1 to 3 indicates the mutation type: 1 for swap (exchanging two genes), 2 for reversion (reversing two genes), and 3 for insertion (moving one gene after another). This mutation occurs on both strings. In the next section, solving, validation, and sensitivity analysis of the proposed model in small sizes were performed in CPLEX. Because of the complexity of the proposed model in the large sizes, the NSGA-II was implemented in MATLAB for this purpose.

4. EXPERIMENTAL RESULTS

4. 1. Data Generation and Parameters' Value

The model's (random) parameters are listed in Table 6. Due to the lack of datasets on the perishable product supply chain problem (considering uncertainty), 25 random input series are provided in Table 7 to evaluate how the different dimensions of inputs affect the model's outputs. Problem inputs involve- the number of incoming and outgoing trucks, the product types' number, the cross-warehouses' number, and the periods' number - each adding complexity. The parameter *M* is used in constraints 7-11, related to time. So, *M* should be greater than or equal to the maximum value of f_{1best}. We chose *M* equal to or greater than 4000 (Table 8).

TABLE 6. Parameters' value

Parameter	The value
w_{iv}	Rand [1 i]
f_{ip}	Randi [1 8]
PU_{pv}	Randi [30 60]
PL_{pv}	Randi [30 60]
l_j	Rand [1 i]
TE	10
dem_p	Randi [100 200]
$\widehat{dem}_p$	Normal(150, 20)
λ_p	Randi [10 20]
pen_{iv}	Rand [1000 2000]
TC_{ijpv}	Randi [1000 2000]
TS	Randi [30 60]
CQ_{ijpv}	Randi [1000 2000]
$W_{kk'}$	Randi [10 20]
Q^{τ}_{ijpv}	Randi [1 6]
θ_{iv}	Randi [100 200]
C_{iv}	Randi [100 200]
d_{iv}	Randi [10 20]
a_{iv}	Randi [10 20]
M	10^4

TABLE 7. The random input series

No.	Input Trucks	Output Trucks	Product Types	Warehouses	Periods
1	10	8	2	1	1
2	11	9	2	1	1
3	12	10	3	2	1
4	13	12	3	2	2
5	14	13	4	2	2
6	15	15	4	3	2
7	16	17	5	3	3
8	17	18	5	4	3
9	18	19	5	4	3
10	20	20	6	5	4
11	22	20	6	5	4
12	24	21	6	5	4
13	25	22	7	6	4
14	26	23	7	6	4
15	27	24	7	6	4
16	28	25	8	7	5
17	29	26	8	7	5
18	30	27	9	7	5
19	30	28	9	8	5
20	30	30	10	8	5
21	30	30	20	10	5
22	50	50	100	15	5
23	50	50	100	20	10
24	50	50	200	20	10
25	50	50	400	30	10

TABLE 8. The NSGAII parameters' level

	N_{Pop}	P_c	P_m	Max_{iter}
1(small)	50	0.8	0.01	50
2(medium)	100	0.9	0.02	80
3(high)	200	0.95	0.05	100

4. 2. Parameter Setting

The effectiveness of the proposed algorithm relies on its parameters. Exhaustively exploring all parameter combinations through factorial experimentation can be lengthy. To streamline this process, a fractional factorial experiment enhanced with the Taguchi method utilizes an orthogonal array to efficiently identify optimal algorithm parameters, reducing the number of experiments required. A Taguchi design assesses the impact of algorithm parameters on the minimal values of two objective functions, while analysis of variance identifies significant parameters. This method distinguishes between desirable controllable factors and undesirable uncontrollable noise factors. Since eliminating noise factors can be challenging, the focus is on minimizing their impact while maximizing the robustness achieved through optimizing controllable factors. Experimental results are quantified using a signal-to-noise ratio (S/N), with a lower ratio indicating better performance. Consequently, the factor level with the highest signal-to-noise ratio represents superior results.

$$\frac{S}{N} = -10log_{10}^{\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{Y_i^2}\right)} \quad (41)$$

where Yi is the performance metric for each trial.

Four NSGA-II parameters, each with three levels, influence two objective functions. A complete factorial design requires eighty-one experimental runs. The Taguchi design defined the parameters: the size of the population (N_{Pop}), the rate of crossover (P_c), the rate of mutation (P_m), and the maximum number of iterations (Max_{iter})- are defined through the Taguchi design.

Table 8 lists these factors and their levels. The Taguchi method will be employed initially for parameter optimization. Table 9 lists the experimental specifications of NSGA-II. The most suitable design for this study is a three-level experimental approach. Under Taguchi's standard orthogonal arrays, the L9 array was selected as the optimal empirical design for parameterizing the algorithm. The L9 array consists of nine runs, with the following results in Table 5. Improved results are obtained with a higher signal-to-noise ratio. The adjusted parameters—Population size (N_{Pop}), Crossover rate (P_c), Mutation rate (P_m), and Maximum Iterations (Max_{iter})—are set to 200, 0.9, 0.01 or 0.02, and 50, as illustrated in Figure 2. The computation on the tenth problem instance was executed by Minitab 22.2.1.

4. 3. Small-Size Problems The Min-Max method on the proposed model is coded in CPLEX. The optimum objective function values generated by IBM ILOG CPLEX 12.6.0.0 are recorded for multi-product and single-product modes. Table 10 includes the optimal objective function values produced in CPLEX as specified in Relations 1 and 2, respectively referred to as the f_{1best} and f_{2best}.

Because of its Np-hardness, the problem's complexity grows with dimensions. According to Table 10, as the problem dimensions increase, so do the models' objective function and calculation time.

TABLE 9. Experimental specification of NSGA-II

No.	N_{Pop}	P_c	P_m	Max_{iter}	NPS
1	1	1	1	1	10
2	1	2	2	2	10
3	1	3	3	3	7
4	2	1	2	3	9
5	2	2	3	1	12
6	2	3	1	2	10
7	3	1	3	2	16
8	3	2	1	3	18
9	3	3	2	1	20

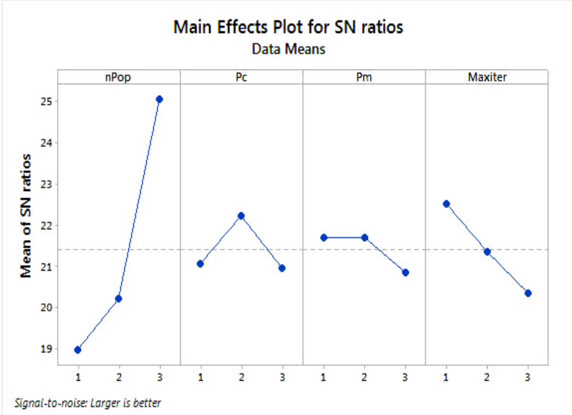

Figure 2. Mean of SN ratios for NSGA-II parameters adjustment

TABLE 10. The Multi-Product and Single-Product Modes best-Recorded Objective Functions

No.	multi-product mode		single-product mode		Elapsed Time (S)
	f_{1best}	f_{2best}	f_{1best}	f_{2best}	
1	131	4286296	118	4271853	11
2	257	4300509	238	4284243	16
3	443	4311065	291	4296742	22
4	599	4324865	406	4310070	27
5	752	4338608	579	4324535	38
6	928	4355784	739	4336255	43
7	1118	4369903	910	4355574	52
8	1313	4385249	1122	4374430	62
9	1468	4402742	1333	4390514	71
10	1658	4418400	1489	4401641	79

NSGA-II validation for Small-scale problems is stated in Table 11 and Table 12.

NSGA-II generates a range of solutions reflecting the compromises in multi-objective problem-solving. While CPLEX is ideal for precise and efficient solutions, NSGA-II is superior for exploring diverse options in multi-objective scenarios, showcasing how these methods complement each other in optimization. According to Table 12, Comparing CPLEX and NSGA-II on small-size problems does not uncover significant performance differences in optimization. NSGA-II Solves the first ten small-scale problems in under a second.

4. 4. Large Size Problems NSGA-II was implemented in MATLAB R2015a for large problem instances, running on a personal computer with an Intel Core i7 processor (2.4 GHz) and 16 GB of RAM. The results are reported in Table 13.

TABLE 11. The value of f_{1best} in NSGA-II VS the exact method

No.	f_{1best} Exact Method	f_{1best} NSGA-II	$\frac{f_{1best-NSGA\,II} - f_{1best-CPLEX}}{f_{1best-NSGA\,II}}$
1	131	415	0.684
2	257	904	0.716
3	443	703	0.369
4	599	767	0.219
5	752	840	0.104
6	928	942	0.014
7	1118	1154	0.032
8	1313	1358	0.033
9	1468	1471	0.002
10	1658	1663	0.003

TABLE 12. The value of f_{2best} in NSGA-II VS the exact method

No.	f_{2best} Exact Method	f_{2best} NSGA-II	$\frac{f_{2best-NSGA\,II} - f_{2best-CPLEX}}{f_{2best-NSGA\,II}}$
1	4286296	4293717	0.002
2	4286296	4305572	0.001
3	4300509	4332502	0.005
4	4311065	4339489	0.003
5	4324865	4342097	0.000
6	4338608	4383480	0.006
7	4355784	4370253	0.000
8	4369903	4390253	0.001
9	4385249	4416754	0.003
10	4402742	4426649	0.002

Verma et al. (39) say researchers commonly use objective function values and solution time to compare NSGA-II with other algorithms; the widely used performance metrics are NPS, Hypervolume (HV), set coverage, Inverted Generational Distance (IGD), Spacing, RNI, GD, and Spread (or Diversity) n the other hand, finding Pareto-optimal solutions for medium—and large-sized problems is infeasible or highly time-consuming e will use three indicators, NPS, Overall Non-dominated Vector Generation (ONVG), and Spacing (S), to assess the proposed algorithm's performance in addressing medium—and large-sized problems these metrics provide a comprehensive view of the algorithm's performance by evaluating the solutions' quality (through NPS and ONVG) and Diversity (through Spacing) the definition and the usage of some of these metrics are as follows. The Number of Pareto Solutions (NPS) counts the number of unique distinct non-dominated solutions on the Pareto front to evaluate the algorithm's ability to explore the Pareto front.

ONVG (Overall Non-dominated Vector Generation) measures the proportion of non-dominated solutions generated by the algorithm compared to the total number of solutions to help evaluate the algorithm's efficiency in producing high-quality solutions.

$$ONVG = |PF_{known}| \tag{42}$$

where PF_{known} represents the obtained approximation front.

Spacing (S) evaluates the uniformity of the solutions across the Pareto front to ensure that the algorithm provides a well-distributed set of solutions, which is crucial for decision-making in multi-objective optimization.

$$S = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2} \tag{43}$$

N is the number of non-dominated solutions, d_i is the distance between the ith solution and its nearest neighbor, $\bar{d}$ is the average distance between all solutions and their nearest neighbors.

Using these indicators is beneficial for several reasons:

Comprehensive Evaluation: These metrics provide a comprehensive view of the algorithm's performance by evaluating the solutions' quality (through NPS and ONVG) and Diversity (through Spacing).

Scalability: For medium- and large-sized problems where finding the exact Pareto front might be infeasible, these metrics offer a practical way to assess the algorithm's effectiveness without requiring the actual Pareto front (39).

Practicality: They are relatively easier to compute than other metrics, like hypervolume, especially for large-size problems (39).

We also consider other factors, such as computational time and the algorithm's robustness across different problem instances.

4. 5. Sensitivity Analysis Sensitive parameters and their effect on the objective functions are determined to be recognized frequently based on what conditions and parameters exist and to what extent sensitivity exists.

To assess the impact of parameter increases (10–50%) on objective function values, a dataset of 100 randomized input series was generated and analyzed. Parameters included product variety, truck loading/unloading times, truck exchange times, lateness fees, quality degradation, and demand uncertainty. For convenient reference, tables and graphs present the average changes in objective functions. In all figures, the vertical axis depicts the increase in objective functions.

TABLE 14. Evaluation metrics in medium and large-size problems

No.	NPS	ONVG	S
11	21	164.19	0.09
12	18	170.27	0.05
13	16	135.19	0.10
14	18	237.60	0.05
15	15	139.59	0.04
16	19	166.65	0.03
17	20	188.69	0.04
18	18	137.54	0.05
19	19	136.24	0.07
20	21	147.87	0.08
21	17	186.87	0.07
22	23	190.18	0.07
23	15	120.80	0.07
24	18	187.92	0.03
25	17	214.00	0.08

Table 15 summarizes how changes in parameters affect tardiness values. According to Table 15, nearly all parameter modifications yield similar results concerning the tardiness value (i.e., the first objective function mentioned in Relation 1).

It is crucial to emphasize that tardiness remains constant regardless of any alterations of the parameters associated with quality degradation and lateness penalty.

The truck switch cost has a minimum impact of 20%, while the other parameters have an approximate effect of 25%. The most influential factors on the outcome are the extended loading time and the expenses associated with truck switching, followed by unloading time and increased product variety.

Table 16 summarizes the comparisons of the impact of parameter changes on the cost values. According to Table 16, the effect of all parameters on the model costs is nearly similar. The most effective parameter is the product type variety, which leads to a 14.5% increase in the model costs.

In Figure 3, the horizontal axis illustrates the percentage increase in the variety of products (in the tenth data series), while the vertical axis depicts the increase in objective functions. The increase in product variety will inevitably lead to higher tardiness and associated costs, including the direct costs of tardiness and quality reduction expenses. In Figure 3, the line graph is placed higher than the dashed one, so the increase in the variety of products creates more sensitivity to tardiness than the cost. With the expansion of product options, we will initially experience a delay and witness the consequential effect of direct and indirect costs.

TABLE 15. Comparing the parameters' effect on tardiness

Parameter Change	%10	%20	%30	%40	50%
Quality	0	0	0	0	0
Trucks Switch Time	0.0706	0.1499	0.2137	0.2451	0.2455
Unload Time	0.0977	0.1852	0.2295	0.2406	0.2405
Product Type	0.0983	0.1868	0.2393	0.2532	0.2435
Load Time	0.1032	0.1559	0.1954	0.2335	0.2490
Transfer Fee	0.1104	0.1625	0.1940	0.2106	0.2124

TABLE 16. Comparing the parameters' effect on cost

Parameter Change	%10	%20	%30	%40	50%
Quality	0.0226	0.0581	0.0791	0.0934	0.1150
Transfer Fee	0.0237	0.0499	0.0749	0.0949	0.1167
Lateness Fee	0.0268	0.0528	0.0832	0.0979	0.1167
unload time	0.0333	0.0615	0.0956	0.1073	0.1214
trucks switch time	0.0319	0.0598	0.0940	0.1169	0.1254
load time	0.0395	0.0722	0.1006	0.1135	0.1254
Product Type	0.0396	0.0788	0.1134	0.1306	0.1446

Figure 4 shows the sensitivity analysis of quality degradation. The line curve represents the variation in tardiness (i.e., Relation 1), and the dashed curve represents the variations in cost (i.e., Relation 2). According to Figure 4, quality degradation does not affect tardiness, but it causes costs to increase exponentially.

Figure 5 shows the sensitivity analysis of the demand uncertainty. According to Figure 5, as the uncertainty of demand rises, so does the cost and tardiness. In this figure, the line curve represents the variation in tardiness (i.e., Relation 1), and the dashed curve represents the variations in cost (i.e., Relation 2). The tardiness escalates more than twice as fast as the cost, which is exponential, demonstrating the significant impact of demand uncertainty on the objective functions.

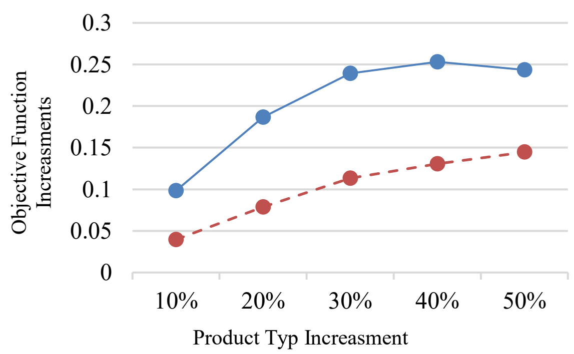

Figure 3. Sensitivity analysis of variety in the product number

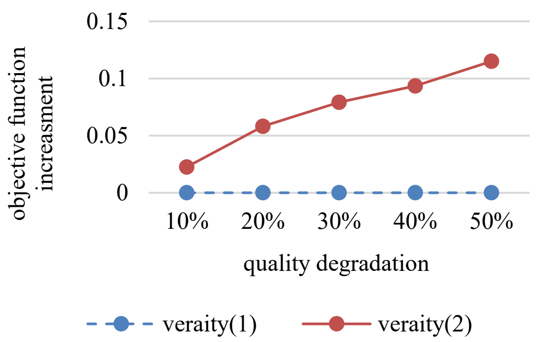

Figure 4. Sensitivity analysis of quality degradation

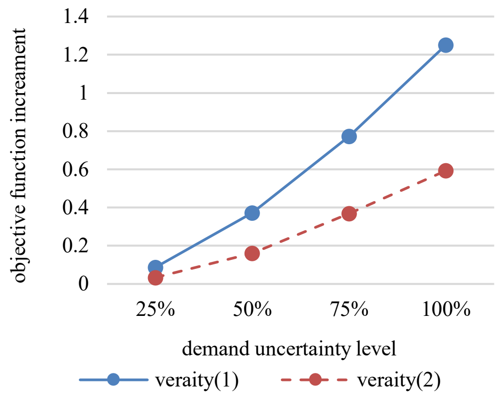

Figure 5. Sensitivity analysis of the demand uncertainty

5. CONCLUSION

This research addresses the need to improve the management of cross-docking warehouses to reduce delay time, minimize costs, and improve customer service. The study examines the challenges associated with managing perishable products that have a limited shelf life but do not spoil immediately. Its primary audience includes producers, distributors, and exporters of these goods, who must maintain product quality to uphold their reputation and avoid financial losses. Some key sectors include exporters of fresh products like medicinal herbs, saffron, and pistachios, flower producers, distributors of large-scale healthy packaged vegetables, and bakery item distributors such as bread and pastries. Each sector faces unique quality conservation challenges that necessitate effective strategies throughout the supply chain. The delay in cross-docking warehouses increases the stoppage time of these products, leading to a decrease in quality. When quality declines, it leads to unnecessary costs. To address this problem, we propose a bi-objective optimization model for scheduling the trucks of perishable products. The first objective function of the model addresses tardiness to affect customer satisfaction and costs, including tardiness fines. By optimizing the scheduling of trucks, costs and delays can be reduced, leading to increased profitability and supplier satisfaction. Therefore, optimizing the proposed model creates a win-win situation for customers and suppliers in the supply chain of perishable products. The uncertainty of demand and the variety of products increased the complexity of problems, prompting the suggestion to use a meta-heuristic algorithm. The results confirm the efficacy and high performance of the NSGA-II algorithm. The findings further show the efficacy of the proposed model. Sensitivity analysis revealed that demand uncertainty significantly affected the model objective functions, particularly in cases of delays. According to the sensitivity analysis results of model parameters, the most influential parameter on the cost was the increasing variety of products. The impact of other parameters on the delays was nearly the same.

It is proposed that the managers of the related sectors, such as the bread supply chain, the pharmaceutical industry, the cut flower supply chain, and others, apply the proposed method to manage the transportation times of their perishable products. In such sectors, managing the transportation time of goods, including tardiness, and minimizing the total transportation time of goods will prevent the deterioration of product quality and related costs. Here are some suggestions for future research:

- Discussing other uncertain parameters and risk factors, in addition to demand uncertainty, such as loading and unloading time, allows decision-makers to evaluate the system's performance more realistically and assess various factors affecting optimal policies.
- Applying uncertainty approaches to model the problem, such as approximate dynamic programming and modern methods based on fuzzy logic and robust optimization.
- Using various innovative solution methods, like heuristics and meta-heuristic algorithms, and comparing their performance and efficiency.
- Providing a stable schedule.
- Implementing the current research model based on a real case study.

Demand is a critical factor in the scheduling problem associated with perishable products, where its inherent uncertainty poses significant challenges. Predicting future demand scenarios is complex due to numerous influencing variables. Traditional methods often fall short of providing reliable forecasts. This inadequacy highlights the need for more advanced techniques. As a managerial insight, leveraging artificial intelligence, particularly artificial neural networks, offers a promising solution for improved demand estimation. These methods utilize historical data patterns, enabling a more precise and scientifically grounded approach to forecasting demand for perishable goods.

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Persian Abstract

چکیده

این مطالعه برنامه ریزی کامیون را برای حمل و نقل محصولات فاسد شدنی تحت عدم قطعیت تقاضا بهینه می کند. زنجیره تامین کالاهای فاسد شدنی به دلیل اهمیت حیاتی کیفیت برای مصرف کنندگان، ذاتاً پیچیده است و چالش های توزیع لجستیکی قابل توجهی را ارائه می دهد که باید به طور موثر مدیریت شوند. رویکرد پیشنهادی در این مطالعه از انبارداری متقاطع استفاده می‌کند، یک استراتژی محبوب که سطح موجودی را کاهش می‌دهد و زمان تحویل را کوتاه می‌کند. این مطالعه یک مدل برنامه ریزی ریاضی دوهدفه غیر قطعی را برای به حداقل رساندن اهداف هزینه و زمان ایجاد می کند. به حداقل رساندن کاهش کیفیت محصول به طور ضمنی در تابع هدف مرتبط با هزینه گنجانده شده است. این مدل همچنین عدم قطعیت ذاتی در تقاضا را در نظر می‌گیرد. همچنین در مدل پیشنهادی که در محیط چند دوره ای تعریف شده است، انواع کامیون‌ها و زمان‌های بارگیری و تخلیه مورد نیاز برای هر نوع محصول متفاوت در نظر گرفته شده است. در نظر گرفتن این فرضیات در کنار هم، مدل توسعه داده شده این مطالعه را از مدل‌های انبارداری متقاطع موجود متمایز می‌کند. برای مسائل در اندازه‌ی کوچک، نرم‌افزار بهینه سازی CPLEX جواب‌های دقیقی ارائه می‌دهد. برای مسائل با اندازه بزرگ، از روش فراابتکاری NSGA-II استفاده می‌شود. مقایسه CPLEX و NSGA-II در مسائل با اندازه کوچک تفاوت عملکرد قابل توجهی را نشان نمی‌دهد. CPLEX در راه حل‌های دقیق برتر است، در حالی که NSGA-II در در نظر گرفتن جایگزین‌های مختلف در سناریوهای چند هدفه بهتر عمل می‌کند. این نشان می‌دهد که چگونه این دو در بهینه‌سازی یکدیگر را تکمیل می‌کنند. برای ارزیابی اثر پارامترهای ورودی بر NSGA-II ، این پارامترها با استفاده از روش تاگوچی بهینه می‌شوند. تجزیه و تحلیل حساسیت نشان می‌دهد که تاثیرپارامترهای مدل بر تاخیر در بازه‌ی 22 تا 25 درصد، و بر هزینه‌های سیستم در بازه‌ی 12 تا 15 درصد قرار دارد. از بین پارامترهای مدل، افزایش تنوع محصولات بیشترین تاثیر را بر جمع وزن داده شده‌ی تاخیرها دارد. در این مدل با کاهش زمان تاخیر، زمان تلف شده و هزینه‌های مرتبط کاهش می‌یابد. کاهش زمان تلف شده درحفظ سطح کیفیت محصولات، و افزایش سطح خدمت‌دهی و رضایتمندی مشتریان تاثیر چشم‌گیری دارد و سودآوری سیستم را افزایش می‌دهد.