Research Annals of Industrial and Systems Engineering

www.raise.reapress.com

Res. Ann. Ind. Syst. Eng. Vol. 2, No. 2 (2025) 154–169.

Paper Type: Original Article

Development of a Scheduling Model for Container Shipping Lines in a Green Supply Chain to Minimize Costs, Considering Port Time Windows and Demand Uncertainty

Shahab Amani*

Department of Industrial Engineering, Faculty of Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran; shahabamani73@gmail.com.

Citation:

Received: 11 June 2024 *Revised: 01 September 2024* *Accepted: 16 November 2024*	Amani, Sh. (2025). Development of a scheduling model for container shipping lines in a green supply chain to minimize costs, considering port time windows and demand uncertainty. *Research annals of industrial and systems engineering, 2*(2), 154-169.

Abstract

In recent years, the increase in Gross Domestic Product (GDP) and global trade has significantly expanded the role of freight transport, particularly maritime transport. Container trade has experienced notable growth, and shipping lines have become one of the most important container transport methods. Proper scheduling of these shipping lines requires precise planning, with factors such as port service availability playing a crucial role. The term "port time window" refers to specific timeframes during which a port can provide services to ships, significantly affecting shipping line schedules. Well-designed schedules not only affect fuel consumption but also contribute to reducing air pollution. However, uncertainty in various parameters can degrade the quality of scheduling outcomes. The present research proposes a scheduling model for container shipping lines within a green supply chain. It aims to minimize transportation costs, fuel consumption, and environmental pollution while considering port time windows and demand uncertainty. Given the complexity and constraints of the problem, it is classified as NP-hard. Small-scale instances are solved using GAMS software, while metaheuristic algorithms are applied to large-scale problems. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are employed for comparison, and results are analyzed regarding solution time and accuracy.

Keywords: Scheduling, Container transport, Shipping lines, Green supply chain, Uncertainty.

1 | Introduction

With industrial progress and economic expansion, domestic and international trade has grown significantly, making freight transport essential. Among different transport methods, maritime transport, especially container trade, plays a key role in global supply chains. In 2012, container transport accounted for over 16%

Corresponding Author: shahabamani73@gmail.com

https://doi.org/10.22105/raise.v2i2.51

Licensee System Analytics. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0).

of global maritime freight, underscoring its importance. Containers transport various goods, including industrial materials, food, and textiles, and are scheduled by shipping companies to ensure timely delivery. Synchronizing ship arrivals and departures with port schedules enables customers to precisely plan their cargo deliveries, reinforcing container shipping as a pillar of global supply chains. However, scheduling ships and planning their routes is challenging and is influenced by several factors, including port service availability. Port service capacity is inherently limited, meaning only a restricted number of ships can receive services at a given time. The port time window defines specific periods during which a port can accommodate ships, making it a critical factor in scheduling. Designing effective shipping schedules without incorporating port time windows is impractical. Thus, robust scheduling mechanisms must be developed to provide fast, safe, and cost-effective shipping.

Uncertainty is inevitable in modern supply chains, affecting nearly all operational parameters. Ignoring demand uncertainty can undermine model reliability, leading to suboptimal decisions. Therefore, incorporating demand uncertainty into supply chain planning is essential, and practical strategies must be devised to mitigate its impact.

The movement of shipping lines follows precise schedules that dictate the departure times of vessels. These schedules directly impact ship speed and fuel consumption, increasing cubically with ship speed. Consequently, this factor is closely linked to environmental pollution. A well-designed schedule can significantly reduce transportation costs, minimize stopovers, and lower fuel consumption.

This research aims to develop an optimized scheduling model for container shipping lines that minimizes vessel operation costs, transportation costs, and environmental emissions. Besides, the scheduling model must account for port time windows and demand uncertainty, as these factors critically affect the reliability of model results. Failure to incorporate uncertainty in demand can lead to erroneous planning decisions and reduced model credibility. Thus, this study proposes a container shipping scheduling model within a green supply chain framework. The primary objective is cost reduction while considering port time constraints and uncertain demand levels. The container routing and scheduling problem is divided into two components: Ship loading and route planning and Freight allocation to demand points. This research primarily focuses on the first component – ship routing and scheduling – by modeling the problem as a Vehicle Routing Problem (VRP). The model incorporates economic objectives (cost minimization) and environmental goals (pollution reduction) while explicitly accounting for port time windows and demand uncertainty.

2 | Literature Review

Given containerized maritime transport's critical role, precise shipping line scheduling has gained substantial research attention in recent years. Numerous studies have examined supply chain scheduling, specifically container transport logistics. This research reviews the literature on green supply chains, demand uncertainty, and transportation scheduling, particularly in containerized maritime shipping.

Despite the significance of schedule optimization in container transit networks, limited studies have considered the combined effect of port time windows, green supply chain principles, and demand uncertainty. Addressing these factors is crucial for improving shipping profitability and enhancing global supply chain efficiency. The primary goal of Supply Chain Management (SCM) is to ensure service reliability while minimizing total system costs, including transportation, shortage, and inventory holding costs. *Fig. 1* provides a conceptual overview of the supply chain network under study.

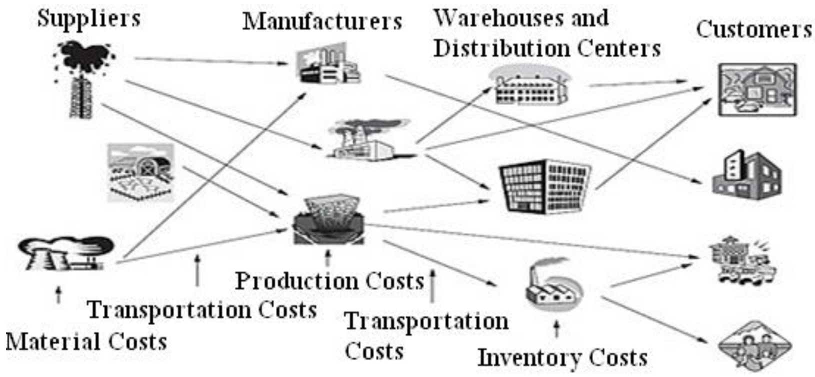

Fig. 1. A conceptual overview of the supply chain network under study.

3 | Previous Studies

De Matos Sá et al. [1] investigated offshore wind farms facing high-reliability challenges and maintenance costs due to their harsh environments. The study proposed a novel maintenance scheduling approach based on wind and wave forecasts, optimizing Operations and Maintenance (O&M) schedules to reduce costs and operational risks. The method improved wind farm profitability by 2–24%, with a case study on WindFloat Atlantic demonstrating its effectiveness.

Ma et al. [2] introduced a two-stage scheduling approach for Active Distribution Networks (ADN), incorporating uncertainty in renewable energy sources and system failures. The first stage aimed to minimize operational costs, while the second focused on minimizing load reduction under emergency conditions. The study employed Particle Swarm Optimization (PSO), and simulation results validated the high efficiency of the proposed method.

Kumar et al. [3] addressed the growing global concern for sustainability in SCM, emphasizing the need for integrating sustainability into decision-making. Their study proposed a network planning model to reduce costs and carbon emissions while ensuring balanced material flow and optimized resource utilization. Moreover, sensitivity analysis was conducted to evaluate the impact of various parameters on system performance.

Gharibi et al. [4] developed a closed-loop logistics network for mobile phone and digital camera after-sales services to maximize profit and minimize environmental impact. Their proposed model, formulated as a Mixed-Integer Linear Programming (MILP) problem, optimized resource allocation and the efficiency of disassembly centers. The results demonstrated that incorporating green factors into network design reduces environmental pollution while increasing profitability.

Utsav et al. [5] explored the integration of predictive algorithms and optimization techniques for solving decision-making problems under uncertainty, a field known as “contextual optimization." Their study introduced various models and methodologies derived from Operations Research (OR) and Machine Learning (ML). The objective was to provide a comprehensive overview of this emerging field and stimulate further advancements in combining ML with probabilistic programming.

Bui et al. [6] focused on enhancing green production in the textile industry. They employed hybrid methods to identify key sustainability factors and their causal relationships. They aimed to construct a reliable hierarchical model with five main aspects and 23 criteria, assisting Vietnam's textile sector adopt more environmentally friendly and sustainable practices.

Chabane et al. [7] introduced a dual-objective model to minimize costs and greenhouse gas emissions. Abdullah et al. [8] proposed a single-objective model considering environmental concerns and pollution permit costs.

Kannan et al. [9] developed a reverse logistics network design, while Chabane's additional work involved a dual-objective closed-loop supply chain model minimizing environmental impact.

Pishva et al. [10] formulated a dual-objective model addressing facility location, capacity, and technology selection, incorporating fuzzy modeling to handle production cost and emission uncertainty.

Giarola et al. [11] used a two-stage stochastic programming approach to model uncertainty in pollution permit pricing, designing a partial supply chain network that did not encompass all supply, production, and distribution levels.

4 | Scheduling and Routing in Containerized Maritime Transport

Christiansen et al. [12] and Meng et al. [13] highlighted that research on scheduling in container shipping networks remains scarce. Their study, which focused on technical-level schedule design, marked some of the earliest work in this domain.

Wang and Meng [14] developed a container scheduling and routing model for a general shipping network with multiple ports and routes.

Qi and Song [15] proposed a schedule optimization model targeting fuel consumption reduction.

Wang and Meng [16] later incorporated uncertainty in port operations and vessel recovery processes, assuming that ships could compensate for delays. They ensured that their models were as close to real-world conditions as possible.

Wang et al. [17] proposed a dynamic programming approach for ship scheduling, incorporating port time windows. Their extended study analyzed recurrent port visits, optimizing schedules based on operational constraints.

Borner et al. [18] investigated scheduled ship recovery, assessing failure scenarios and activity-balancing strategies to enhance resilience in maritime operations.

Homayouni et al. [19] analyzed carbon regulation mechanisms and their impact on sustainable green supply chains. Using a multi-objective planning model, they evaluated carbon reduction strategies, comparing carbon tax policies and cap-and-trade mechanisms. The findings suggest that cap-and-trade policies are more effective and better suited to managing uncertainties when supported by government incentives.

Coşkun et al. [20] examined the impact of uncertainties on supply chain resilience and the role of information sharing. Their results indicate that non-technological uncertainties (except technology) negatively affect supply chain resilience, and high-level information sharing with suppliers can have adverse effects. The study emphasizes the need for proactive strategies to maintain supply chain resilience.

Sun et al. [21] proposed a renewable energy integration model incorporating carbon capture technologies and demand-side management. Their model successfully reduces costs and carbon emissions while optimizing electricity distribution and load management, contributing to low-carbon energy goals.

Wang [22] focused on promoting green agricultural transformation by addressing supply chain instability under demand and output uncertainties. Using a Stackelberg game model and profit-sharing contracts, they optimized and coordinated the agricultural supply chain, improving overall revenue and ensuring sustainable operations.

5 | Research Methodology

This study develops a scheduling model for containerized shipping lines within a green supply chain, aiming to minimize costs while considering port time windows and demand uncertainty. Due to the sensitive nature of transported goods, maritime transport requires precise planning. Various logistics and maritime transport approaches have been examined, revealing the need for further research to develop more efficient models.

This section introduces an enhanced scheduling model compared to previous studies, outlining the research methodology and proposed model.

The container routing and scheduling problem is divided into two main components:

I. Ship loading and route planning: Determines the optimal routes that the fleet must follow to reach its destination.

II. Cargo allocation and unloading: Optimizes cargo distribution to demand points.

This research focuses on the first component-ship routing and scheduling-which involves planning ship loading and defining optimal routes, modeled as a VRP. The locations where goods can be loaded consist of loading terminals (L). Various product types (O) are transported using containers, each with different capacities.

Fig. 2 illustrates the routing and scheduling problem model for cargo loading planning. Each loading center can load one or two types of products. Furthermore, each container has a different capacity. All containers have a designated origin and, after traversing various routes, ultimately arrive at a specific destination and port. The starting point is considered as (s) and the endpoint as (g). Along the way, ships pass through several intermediate points and cover demand points en route. Various configurations, such as opened routes, different origins, and diverse destinations, can be implemented within the model, which offers this flexibility.

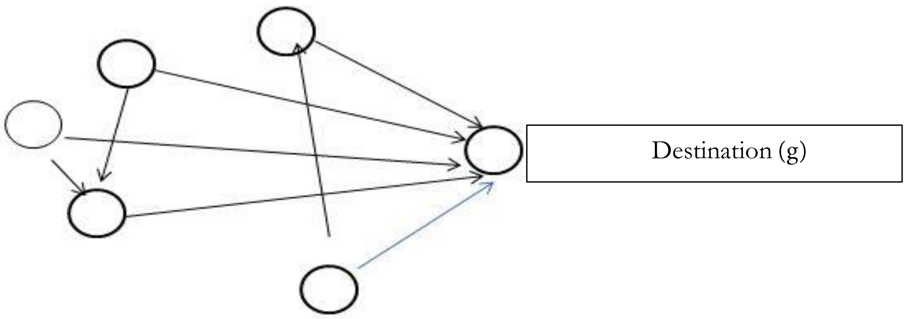

Fig. 2. Schematic representation of container ship routing and scheduling.

5.1 | Problem Characteristics and Proposed Model

The distance between loading points, represented as d_{ij}, is asymmetric, meaning that $d_{ij} = d_{ji}$. However, the triangle inequality holds:

$$d_{i,j+}d_{j,k} \geq d_{i,k}.$$

The set of available containers is denoted as T, each with a fixed and predefined capacity. Moreover, the demand for goods is uncertain and modeled using fuzzy logic. The total demand volume for each product type $o \in O$ is denoted as $\widetilde{D_O}$, where supply chain providers specify demand as fuzzy values every month.

Thus, the problem involves multiple products with diverse types and focuses on solving a container fleet's routing and scheduling problem with limited capacity and loading constraints to optimize allocation, routing, and loading volume. This model aims to minimize total costs while accounting for demand uncertainty.

In addition, the model considers environmental concerns. The shipping fleet must comply with certain environmental regulations and constraints in container transportation, which will be addressed later. Another key issue in this model is time windows. Ships cannot depart anytime they wish, as ports have limited capacity.

Therefore, the time window constraint is also incorporated into this model. The objective function aims to minimize the total operational costs of containers over one month. Total costs include inventory holding costs on ships and terminal-related costs, which depend on the number of stops made at terminals.

Furthermore, this problem assumes the existence of only one origin terminal and one destination terminal. To enhance focus and enable more precise planning, all movements are believed to start from a specified origin, pass through intermediate demand points, and end at a designated destination, completing the transportation process. The problem is formulated as a MILP model.

Table 1. Model sets.

Row	Notations	Description
1	L	Loading and unloading locations
2	O	Product type
3	T	Set of containers

Table 2. Indexes.

Row	Notations	Description
1	g	End point of ship's movement
2	I,j	Loading and unloading locations
3	k	Container
4	o	Product type
5	s	Starting point of movement $g \neq s$

Table 3. Decision variables.

Row	Notations	Description
1	$q_{k,i,o}$	Amount of product type o at loading location i for container k
2	$t_{k,i}$	Loading operation time at location i for container k
3	$x_{k,i,j}$	Binary variable that takes the value of 1 if container k visits loading locations i and j, and 0 otherwise
4	$\delta_{k,i,j}$	Binary variable that takes the value of 1 if container k involves loading location i, and otherwise 0

Table 4. Parameters.

Row	Notations	Description
1	c_i	Charging cost due to occupying location i
2	C_k^{max}	Maximum capacity of container k
3	$d_{i,j}$	Distance between loading location i and loading location j
4	D_o	Uncertain demand for products o
5	$E_{k,i,j}$	Transport time from location i to location j for container k
6	M	A large positive number
7	q_i^{min}	Minimum feasible loading and unloading volume at location i
8	q_i^{max}	Maximum feasible loading and unloading volume at location i
9	w_1	Weight factor for the total distance traveled by containers
10	w_2	Weight factor for the total costs incurred from passing through loading points
11	τ_m	Maximum number of loading locations that a container can visit
12	$\eta_{i,o}$	Binary constant that is 1 if product o can be loaded at location i, and 0 otherwise.
13	FC_k^{min}	Minimum fuel consumption per container
14	FC_k^{max}	Maximum fuel consumption per container
15	α_k	Fuel consumption coefficient per container
16	$t_{k,i}^{min}$	Minimum time required for container k operations at location i
17	$t_{k,i}^{max}$	The maximum time needed for container k operations at location i.
18	$D_{k,O}$	The maximum amount of product type o that can be transported to prevent environmental pollution by container k, which is determined based on environmental regulations.
20	β_k	Carbon dioxide conversion factor for container k

5.2 | Objective Function

The objective function consists of two main components:

I. Minimizing total distance traveled by containers.

II. Minimizing total port loading charges.

Each component is weighted based on expert judgment, leading to the following formulation:

$$\min w_1 \left(\sum_{k\in T}\sum_{i\in L\cup\{S\}}\sum_{j\in L\cup\{g\}} d_{i,j}\; x_{k,i,j}\right) + w_2 \left(\sum_{k\in T}\sum_{i\in L} c_i\; \delta_{k,i}\right).$$

Constraints:

s.t.

$$\sum_{k\in T}\sum_{i\in L} q_{k,i,o} = \widetilde{D_o}, \quad \text{for all } o \in O. \tag{1}$$

$$\delta_{k,j} \quad (\text{for all } k \in T, \text{for all } j \in L \cup \{g\}), i \neq j, \sum_{i\in L\cup\{S\}} x_{k,i,j}, \tag{2}$$

$$\delta_{k,i} \quad (\text{for all } k \in T, \text{for all } j \in L \cup \{s\}), i \neq j, \sum_{j\in L\cup\{g\}} x_{k,i,j}, \tag{3}$$

$$\sum_{i\in L} x_{k,s,i} = 1, \quad (\text{for all } k \in T), \tag{4}$$

$$\sum_{i\in L} x_{k,ig} = 1, \quad (\text{for all } k \in T), \tag{5}$$

$$\sum_{i\in L} \delta_{k,i} \leq \tau_m, \quad (\text{for all } k \in T), \tag{6}$$

$$t_{k,i} + E_{k,i,j} - t_{k,j} - M\,(1 - x_{k,i,j}) \leq 0, \quad (\text{for all } k \in T, \text{for all } i \in L \cup \{s\}, \text{for all} j \in L \cup \{g\}), \tag{7}$$

$$\sum_{i\in L}\sum_{o\in O} q_{k,i,o} \leq C_k^{max}, \quad (\text{for all } k \in T), \tag{8}$$

$$\delta_{k,i}\, q_i^{min} \leq \sum_{o\in O} \eta_{i,o}\, q_{k,i,o}, \quad (\text{for all } k \in T, \text{for all } i \in L), \tag{9}$$

$$\sum_{o\in O} \eta_{i,o}\, q_{k,i,o} \leq \delta_{k,i}\, q_i^{max}, \quad (\text{for all } k \in T, \text{for all } i \in L), \tag{10}$$

$$t_{k,i} \geq t_{k,i}^{min}\, \delta_{k,i,j}, \quad \text{for all } i, k, i \neq s, \tag{11}$$

$$t_{k,i} \leq t_{k,i}^{max}\, \delta_{k,i,j}, \quad \text{for all } i, k, i \neq s, \tag{12}$$

$$\sum_{\mathbf{i=1}} q_{k,i,o} \leq D_{k,O}, \quad \text{for all } k, \tag{13}$$

$$\alpha_k E_{k,i,j} \geq FC_k^{min} x_{k,i,j}, \quad \text{for all } k, \tag{14}$$

$$\alpha_k E_{k,i,j} \leq FC_k^{max} x_{k,i,j}, \quad \text{for all } k, \tag{15}$$

$$\beta_k E_{k,i,j} \leq FC_k^{max} x_{k,i,j}, \quad \text{for all } k, \tag{16}$$

$$x_{k,i,j} \in \{0,1\}, \quad (\text{for all } k \in T, \text{for all } i \in L \cup \{s\}, \text{for all} j \in L \cup \{g\}), \tag{17}$$

$$\delta_{k,i} \in \{0,1\}, \quad (\text{for all } k \in T, \text{for all } i \in L \cup \{s\} \cup \{g\}), \tag{18}$$

$$q_{k,i,o} \geq 0, \quad (\text{for all } k \in T, \text{for all } i \in L, \text{for all } o \in O), \tag{19}$$

$$t_{k,i} \geq 0, \quad (\text{for all } k \in T, \text{for all } i \in L \cup \{s\} \cup \{g\}). \tag{20}$$

Constraint (1) represents the total demand constraint. *Constraints (2)* and *(3)* indicate the allocation constraints at loading locations. *Constraints (4)* and *(5)* state that each container starts operating from an initial point, s, and ends its journey at a final point, g, passing through several ports along the way. *Constraint (6)* specifies that the number of times a port engages in loading operations must be less than or equal to the maximum allowable number of operations.

A classical constraint in the Traveling Salesman Problem (TSP) is the subtour elimination constraint, which is also applicable in this study. *Constraint (7)* represents this constraint, where M is a large positive number and serves as an upper bound for each container's difference in loading dates. *Constraint (8)* states that the transported cargo must not exceed the maximum allowable limit.

In addition, at each loading and unloading location, the cargo volume must remain within a permitted range between the minimum and maximum allowable limits. This restriction is expressed through *Constraints (9)* and *(10)*.

Constraints (11) and *(12)* pertain to time window constraints. *Constraint (11)* sets the minimum, while *Constraint (12)* defines the maximum allowable time for loading operations based on the specified time window. *Constraint (13)* is an environmental constraint related to the green supply chain. This constraint limits the amount of toxic materials and gas emissions from container transportation to a predefined threshold established by the environmental authority.

Due to environmental concerns, fuel consumption in container transportation must not exceed a specified limit. Moreover, a minimum fuel must be consumed for ship movement and cargo delivery. *Constraints (14)* and *(15)* define the permissible fuel consumption based on specified standards.

Constraint (16) limits the allowable carbon dioxide emissions from container transportation. *Constraints (17)–(20)* define the conditions for each variable.

This research introduces fuzzy demand uncertainty compared to the baseline model used in prior studies, whereas previous models assumed deterministic demand.

6 | Analysis

6.1 | Genetic Algorithms

Genetic Algorithms (GA) are a search technique in computer science used to find approximate solutions for optimization and search problems. They are a specific type of evolutionary algorithm that utilizes evolutionary biology techniques such as inheritance and mutation. This algorithm was first introduced by John Holland [23].

In essence, GA apply Darwinian principles of natural selection to find optimal formulas for prediction or pattern matching. GA are often a strong choice for regression-based forecasting techniques. In artificial intelligence, a GA is a programming technique that employs genetic evolution as a problem-solving model. The problem to be solved consists of inputs that are transformed into potential solutions through a process inspired by genetic evolution. These solutions serve as candidates and are evaluated using a fitness function. If the termination condition is met, the algorithm halts. GA are generally iterative, and many of their components involve stochastic processes [23].

GA consist of the following components: Fitness function, representation, selection, and variation. GA are a type of randomized search algorithm inspired by nature. GA have successfully solved classical optimization problems, including linear and convex problems, but they are significantly more effective for solving discrete and nonlinear problems. One example is the TSP. In nature, the combination of superior chromosomes results in better generations, and occasionally, mutations occur in chromosomes that might enhance the next generation. GA apply this same principle to problem-solving.

The process of using GA is as follows:

I. Introducing the problem solutions as chromosomes.

II. Defining the fitness function.

III. Generating the initial population.

IV. Introducing selection operators.

V. Introducing reproduction operators.

An initial set of solutions is generated randomly or algorithmically in GA. This set of solutions is called the initial population, and each solution is referred to as a chromosome. Then, using GA operators, the best chromosomes are selected, combined, and mutated. Finally, the current population merges with the new population, which results from the combination and mutation of chromosomes.

The engine of the GA generates an initial population of formulas. Each individual is tested against a dataset, and the most suitable individuals (typically 10% of the fittest) are retained while the rest are discarded. The fittest individuals undergo crossover (gene exchange) and mutation (random changes in DNA elements). Over multiple generations, the GA moves toward creating increasingly precise formulas. While neural networks are also nonlinear and nonparametric, the significant advantage of GA is that the results are more observable. The final formula is visible to the human user, and conventional statistical techniques can be applied to assess confidence levels in the results. GA technology is continuously improving. For example, introducing virus equations alongside formulas will challenge weaker solutions, strengthening the overall population. Generally, solutions are represented in binary form as 0s and 1s, but other representation methods also exist. Evolution begins with a completely random set of entities and continues across successive generations. In each generation, the fittest individuals are selected, though not necessarily the best.

A solution to the given problem is represented as a list of parameters called chromosomes or genomes. Chromosomes are typically displayed as simple data strings, though other data structures may also be used. Initially, multiple characteristics are randomly generated to create the first generation. Each generation's characteristic is evaluated, and its fitness value is measured using the fitness function.

The next step is to create the second population generation based on selection processes and reproduction from selected individuals using genetic operators: chromosome crossover and mutation.

For each individual, a pair of parents is selected. The selection process is designed so that the fittest elements are chosen, but even the weakest elements have a chance of selection to prevent convergence to a local optimum. Several selection methods exist, including roulette wheel selection and tournament selection. GA typically have a crossover probability ranging between 0.6 and 1, determining the likelihood of offspring production. Organisms recombine based on this probability. The crossover of two chromosomes results in offspring added to the next generation. This process continues until suitable candidate solutions are found in the next generation. The next step involves mutating the newly generated offspring. GA apply a small, fixed mutation probability, usually around 0.01 or lower. Based on this probability, the offspring chromosomes are randomly altered or mutated, particularly through bit mutations in the chromosome data structure.

This process leads to a new generation of chromosomes that differs from the previous one. The evolutionary cycle continues with selection, crossover, and mutation until a stopping condition is met.

Stopping conditions in GA

I. A fixed number of generations is reached.

II. The computational budget is exhausted (e.g., time/money constraints).

III. A solution meets the minimum fitness criteria.

IV. The population reaches a fitness plateau (no further improvement).

V. Manual intervention or inspection.

VI. Any combination of the above conditions.

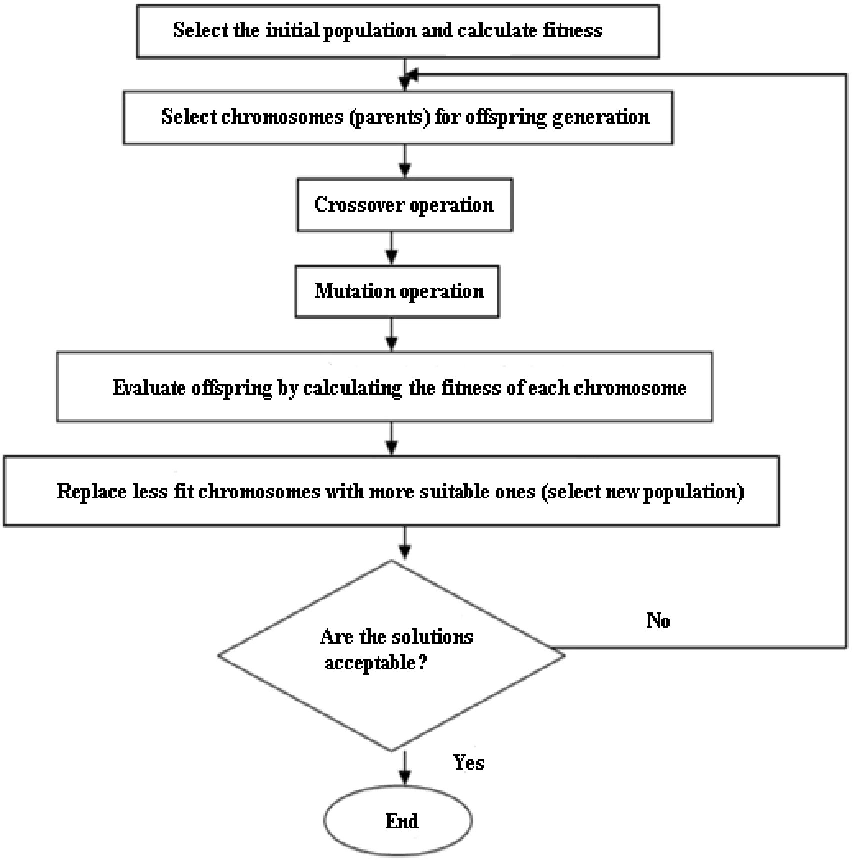

Fig. 3. GA flowchart.

6.2 | Particle Swarm Optimization

Introduced by Eberhart and Kennedy [24], PSO is a population-based stochastic optimization technique inspired by the social behavior of birds flocking in search of food.

A flock of birds searches randomly for food within a given space. There is only one piece of food in this space, and none of the birds knows its exact location. One of the best strategies is to follow the bird closest to the food. This strategy forms the essence of the algorithm. Each solution, referred to as a particle, corresponds to a bird in the collective movement pattern of birds. Each particle has a fitness value computed by a fitness function. The closer a particle is to the target – analogous to food in the bird movement model – the higher its fitness value. Besides, each particle has a velocity that determines its movement. A particle moves through the problem space by following the optimal particles at any moment. This way, a PSO is randomly initialized and attempts to find the optimal solution by updating generations. Each particle updates its state at each step based on two best-known values. The first is the best position the particle has ever achieved, which is recorded and stored. This value is referred to as pbest. The second value the algorithm uses is the best position found so far by the entire swarm, denoted as gbest [25].

Once these best values are determined, the velocity and position of each particle are updated using the following equations:

$$\mathrm{v}[] = \mathrm{v}[] + \mathrm{c1} * \mathrm{rand}() * (\mathrm{pbest}[] - \mathrm{position}\,[]) + \mathrm{c2} * \mathrm{rand}() * (\mathrm{gbest}[] - \mathrm{position}[]).$$

$$\mathrm{position}[] = \mathrm{position}[] + \mathrm{v}[].$$

The right-hand side of *Eq. (1)* consists of three components. The first term represents the particle's current velocity. In contrast, the second and third terms adjust its velocity and steer it toward its personal best experience and the best experience of the entire swarm. Suppose the first term of this equation is ignored. In that case, the velocity of the particles will only depend on their current position, their best personal experience, and the best experience of the swarm. In this case, the best particle in the swarm will remain in its position while the others move toward it. Consequently, the swarm movement without the first term of *Eq. (1)* leads to a process where the search space gradually shrinks, and a local search is performed around the best particle. On the other hand, if only the first term of *Eq. (1)* is considered, the particles continue their usual movement until they reach the boundary of the search space, effectively performing a global search. The pseudocode and flowchart of the PSO algorithm can be seen in *Figs. 2* and *3*.

Table 5. Pseudocode of the PSO algorithm.

For each particle
Initialize particle
End For
Do
For each particle
Calculate the fitness value of the particle fp
/*updating particle's best fitness value so far)*/
If fp is better than pBest
set current value as the new pBest
End For
/*updating population's best fitness value so far)*/
Set gBest to the best fitness value of all particles
For each particle
Calculate particle velocity according to equation (1)
Update particle position according to equation (2)
End For While maximum iterations OR
minimum error criteria are not attained

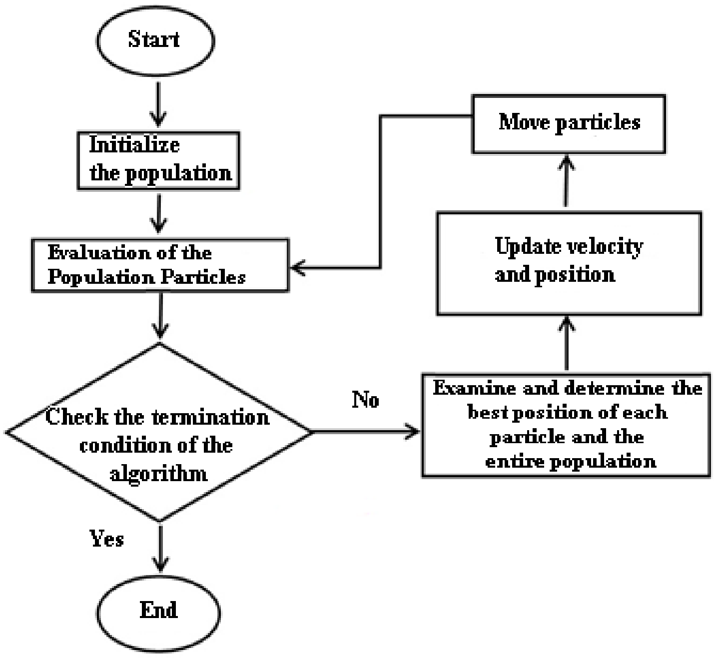

Fig. 4. Flowchart of the PSO algorithm.

7 | Algorithm Configuration for the Research Problem

7.1 | Initial Solution Generation

This section aims to develop algorithms based on genetic and PSO approaches to solve the problem model. Initially, an initial solution must be generated. At all stages, the solution must satisfy the given constraints. The algorithms are then applied to solve the problem. The solution in this algorithm is represented as a sequence. The core idea for generating the initial solution is that each container visits the loading locations with the smallest unfulfilled demand and loads as much as possible until the container's capacity is filled. Certain conditions must be considered to ensure a feasible initial solution.

Objective function evaluation

This research uses the objective function to evaluate and assess new solutions. The algorithm's basis for evaluating and replacing new solutions is the following function:

$$w_1\left(\sum_{k\in T}\sum_{i\in L\cup\{S\}}\sum_{j\in L\cup\{g\}} d_{i,j}\, x_{k,i,j}\right)+w_2\left(\sum_{k\in T}\sum_{i\in L} c_i\, \delta_{k,i}\right).$$

Neighborhood generation

The main idea for generating a neighborhood is inspired by the mutation operator used in GA. One element from the initial solution is randomly selected, and a new random value within the allowable range is assigned.

The quality of the new solution is then evaluated using the objective function, and based on the steps of the metaheuristic algorithm, it may either be accepted or rejected.

Numerical problem solving

Problems of varying sizes were solved in MATLAB to validate the effectiveness of the proposed algorithms.

Table 6. Results of solving problems of different sizes.

Problem	GAMS			GA			PSO		
	Z(×1000 USD)	T(S)	GAP (%)	Z(×1000 USD)	T(S)	GAP (%)	Z(×1000 USD)	T(S)	GAP (%)
O-3-j-5	66.5	20	0	66.5	4.6	0	66.5	5.1	0
O-5-j-5	122.1	21.6	0	122.1	5.2	0	122.1	5.5	0
O-8-j-5	122	23.7	0	122	6.5	0	122	6.4	0
O-10-j-5	131.6	25.6	0	131.6	7.5	0	131.6	7.6	0
O-15-j-5	176.3	26.1	0	184.6	8.3	4	188.3	8.4	6.8
O-18-j-5	201.568	27.2	0	209.5	8.8	4	214.8	9.1	6.5
O-20-j-5	236.8	28.4	0	245.7	9.5	3.75	246.8	9.3	4.2
O-25-j-5	392	28.3	0	396.4	10.4	1.1	401.7	10.2	2.5
O28-j-5	670.5	30.6	0	681.2	11.6	1.6	688.3	12.1	2.6
O30-j-5	682.8	33.4	0	696.2	12.4	2	701.4	13.1	2.7
O33-j-5	708.6	35.8	0	716.1	12.8	1	719.4	12.9	1.5
O33-j-8	720	37.8	0	730.4	14.2	1.5	735.4	14.5	2.1
O30-j-8	768	38.5	0	776.7	15.7	1.1	781.2	15.3	1.7
O30-j-10	854	40.2	0	865	17.3	1.3	869.8	16.9	1.85
O35-j-13	1006	44.8	0	1026	19.2	2	1034.3	19.1	2.8
O35-j-15	1138	46.8	0	1151	21.4	1.1	1160	21.1	1.9
O40-j-18	1428	48.3	0	1447	22.3	1.3	1461	22.5	2.3
O40-j-20	1508	49.6	0	1528	23.1	1.3	1543	23.6	2.3
Average	607.4	33.7	0	616.5	12.8	1.5	621.54	12.94	2.32

Based on the results obtained from solving problems of different sizes, the following key observations can be made:

I. The GA requires less computation time than the other two approaches.

II. The GA solution is closer to the optimal solution than the other methods.

III. Both GA and PSO efficiently solve large-scale problems in less than 30 seconds.

Comparison of optimization approaches

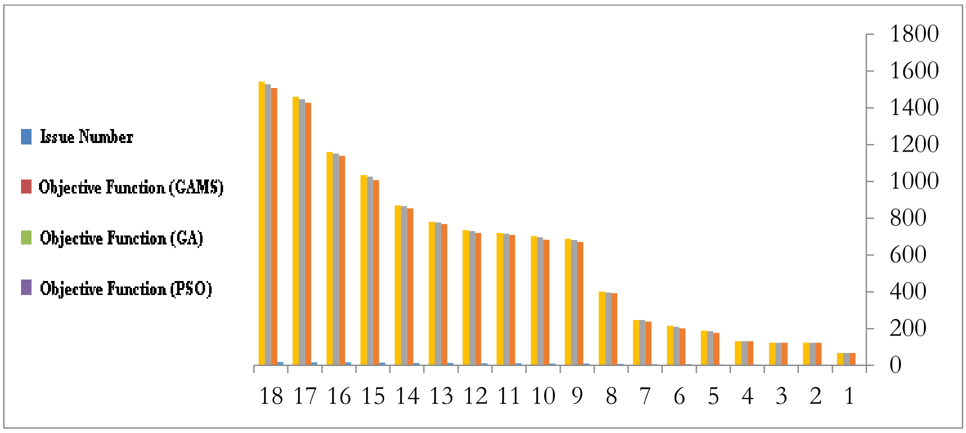

Fig. 5. Comparison of objective function values across three approaches.

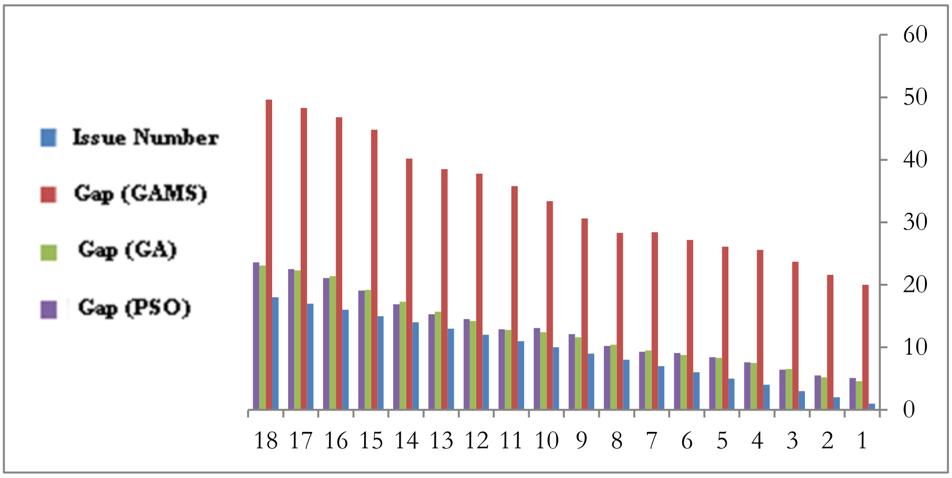

Fig. 6. Comparison of solution time for different approaches.

Fig. 7. compares the three presented approaches in terms of the difference between the obtained solution and the optimal value of the objective function.

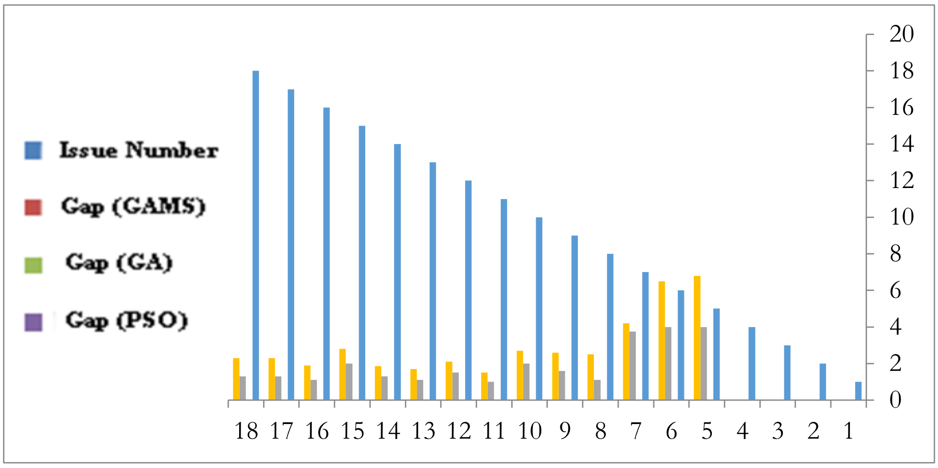

Fig. 7. Comparison of solution gap relative to optimal objective.

8 | Conclusion

This research focuses on developing a scheduling model for container shipping lines within the green supply chain, aiming to minimize costs while considering port time windows and demand uncertainty. In the previous chapters, various model developments have been thoroughly examined, and the steps of the work have been fully explained. This chapter summarizes the activities, results, and interpretations of the research. Moreover, suggestions for better utilization of the model and recommendations for researchers in related fields are provided.

Initially, a comprehensive analysis of existing sources, including books, articles, and dissertations, was conducted to understand the research foundations fully. Reviewing the literature and identifying the strengths and weaknesses of previous studies provided a solid basis for this research. The final proposed model included an objective function to minimize the total costs of the ship, transportation costs, fuel costs, and environmental pollution. The main innovations of the model are:

I. Considering demand uncertainty.

II. Addressing port time windows.

III. Evaluating environmental aspects.

To validate the model, a sample problem was solved using GAMS software. Due to the problem's NP-hard nature, GA and PSO were used to solve larger-scale problems. The obtained results demonstrated the effectiveness of these algorithms.

In conclusion, several points and recommendations regarding this research should be highlighted: The numerical results indicate the high efficiency of the proposed algorithm in solving large-scale problems within a reasonable time. Furthermore, considering port time windows in this problem significantly helps align the model with real-world conditions. Moreover, demand uncertainty, one of the critical issues in the supply chain, has been incorporated into the model, further increasing its real-world applicability. Pollution and green supply chain issues have also been considered in the model to adequately address environmental concerns in the supply chain, which is one of the prominent topics in the production space.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

All data generated or analyzed during this study are included in this published article. No additional data are available.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] De Matos Sá, M., da Fonseca, F. X. C., Luís, A., & Castro, R. (2024). Optimising O&M scheduling in offshore wind farms considering weather forecast uncertainty and wake losses. *Ocean engineering*, *301*, 117518. https://doi.org/10.1016/j.oceaneng.2024.117518

[2] Ma, H., Liu, Z., Li, M., Wang, B., Si, Y., Yang, Y., & Mohamed, M. A. (2021). A two-stage optimal scheduling method for active distribution networks considering uncertainty risk. *Energy reports*, *7*, 4633–4641. https://doi.org/10.1016/j.egyr.2021.07.023

[3] Kumar, A., & Kumar, K. (2024). An uncertain sustainable supply chain network design for regulating greenhouse gas emission and supply chain cost. *Cleaner logistics and supply chain*, *10*, 100142. https://doi.org/10.1016/j.clscn.2024.100142

[4] Gharibi, K., & Abdollahzadeh, S. (2025). A mixed-integer linear programming approach for circular economy-led closed-loop supply chains in green reverse logistics network design under uncertainty. *Journal of enterprise information management*, *38*(1), 1–31. https://doi.org/10.1108/JEIM-11-2020-0472

[5] Sadana, U., Chenreddy, A., Delage, E., Forel, A., Frejinger, E., & Vidal, T. (2023). *A survey of contextual optimization methods for decision making under uncertainty*. https://doi.org/10.48550/arXiv.2306.10374

[6] Bui, T. D., Nguyen, T. T. V., Wu, K. J., Lim, M. K., & Tseng, M. L. (2024). Green manufacturing performance improvement under uncertainties: An interrelationship hierarchical model. *International journal of production economics*, *268*, 109117. https://doi.org/10.1016/j.ijpe.2023.109117

[7] Chaabane, A., Ramudhin, A., & Paquet, M. (2011). Designing supply chains with sustainability considerations. *Production planning & control*, *22*(8), 727–741. https://doi.org/10.1080/09537287.2010.543554

[8] Abdallah, T., Farhat, A., Diabat, A., & Kennedy, S. (2012). Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment. *Applied mathematical modelling*, *36*(9), 4271–4285. https://doi.org/10.1016/j.apm.2011.11.056

[9] Kannan, D., Diabat, A., Alrefaei, M., Govindan, K., & Yong, G. (2012). A carbon footprint based reverse logistics network design model. *Resources, conservation and recycling*, *67*, 75–79. https://doi.org/10.1016/j.resconrec.2012.03.005

[10] Pishva, N., Parsa, G., Saki, F., & Saki, M. R. (2012). Intraventricular hemorrhage in premature infants and its association with pneumothorax. *Acta medica iranica*, 473–476. https://acta.tums.ac.ir/index.php/acta/article/view/3933

[11] Giarola, S., Shah, N., & Bezzo, F. (2012). A comprehensive approach to the design of ethanol supply chains including carbon trading effects. *Bioresource technology*, *107*, 175–185. https://doi.org/10.1016/j.biortech.2011.11.090

[12] Christiansen, M., Fagerholt, K., Nygreen, B., & Ronen, D. (2013). Ship routing and scheduling in the new millennium. *European journal of operational research*, *228*(3), 467–483. https://doi.org/10.1016/j.ejor.2012.12.002

[13] Meng, Q., Wang, S., Andersson, H., & Thun, K. (2014). Containership routing and scheduling in liner shipping: overview and future research directions. *Transportation science*, *48*(2), 265–280. https://doi.org/10.1287/trsc.2013.0461

[14] Wang, S., & Meng, Q. (2011). Schedule design and container routing in liner shipping. *Transportation research record*, *2222*(1), 25–33. https://doi.org/10.3141/2222-04

[15] Qi, X., & Song, D. P. (2012). Minimizing fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times. *Transportation research part e: Logistics and transportation review*, *48*(4), 863–880. https://doi.org/10.1016/j.tre.2012.02.001

[16] Wang, S., & Meng, Q. (2012). Robust schedule design for liner shipping services. *Transportation research part e: logistics and transportation review*, *48*(6), 1093–1106. https://doi.org/10.1016/j.tre.2012.04.007

[17] Wang, S., & Meng, Q. (2012). Liner ship route schedule design with sea contingency time and port time uncertainty. *Transportation research part b: Methodological*, *46*(5), 615–633. https://doi.org/10.1016/j.trb.2012.01.003

[18] Brouer, B. D., Dirksen, J., Pisinger, D., Plum, C. E. M., & Vaaben, B. (2013). The vessel schedule recovery problem (VSRP)-A MIP model for handling disruptions in liner shipping. *European journal of operational research*, *224*(2), 362–374. https://doi.org/10.1016/j.ejor.2012.08.016

[19] Homayouni, Z., Pishvaee, M. S., Jahani, H., & Ivanov, D. (2023). A robust-heuristic optimization approach to a green supply chain design with consideration of assorted vehicle types and carbon policies under uncertainty. *Annals of operations research*, *324*, 1–41. https://doi.org/10.1007/s10479-021-03985-6

[20] Coşkun, A. E., & Erturgut, R. (2024). How do uncertainties affect supply-chain resilience? The moderating role of information sharing for sustainable supply-chain management. *Sustainability*, *16*(1), 131. https://doi.org/10.3390/su16010131

[21] Sun, H., Zou, H., Wen, J., Ke, W., & Kou, L. (2024). Optimal scheduling considering Carbon capture and demand response under uncertain output scenarios for wind energy. *Sustainability*, *16*(3), 970. https://doi.org/10.3390/su16030970

[22] Wang, Q., Ni, M., Wen, W., Qi, R., & Zhang, Q. (2024). Study on sustainable operation mechanism of green agricultural supply chain based on uncertainty of output and demand. *Sustainability*, *16*(13), 5460. https://doi.org/10.3390/su16135460

[23] Holland, J. H. (1992). Genetic algorithms. *Scientific American*, *267*(1), 66–73. https://www.jstor.org/stable/24939139

[24] Eberhart, R., & Kennedy, J. (1995). Particle swarm optimization. *Proceedings of the IEEE international conference on neural networks* (Vol. 4, pp. 1942–1948). IEEE. https://doi.org/10.1109/MHS.1995.494215

[25] Hereford, J. M. (2006). A distributed particle swarm optimization algorithm for swarm robotic applications. *2006 Ieee international conference on evolutionary computation* (pp. 1678–1685). IEEE. https://doi.org/10.1109/CEC.2006.1688510