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Optimization of Multi-Commodity Routing with Dynamic Warehouse Management, Vehicle Ownership Strategies, and Congestion Control

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Abstract

This study optimizes the multi-commodity routing problem in a constrained network, integrating dynamic warehouse management, diverse vehicle ownership options, and congestion management. The model addresses the efficient routing of goods with limited vehicle and warehouse capacities, enabling the addition or removal of warehouses based on demand fluctuations. It incorporates a hybrid fleet strategy, balancing owned and outsourced vehicles to minimize costs while ensuring flexibility. The model also considers network congestion, optimizing routes and schedules to mitigate delays. This approach provides a comprehensive solution for cost-effective and responsive supply chain logistics. In this research, the complexity of the mathematical model and its multi-objective nature led to the use of the epsilon constraint method and the MOGWO and NSGA II algorithms in the model. Solving the model using the mentioned methods showed that the total costs increased with the improvement of the second objective function. This problem has been due to the use of vehicles with higher speeds and higher prices, and also by reducing the risk of transporting products, the total costs have increased again.

Keywords: location-routing, uncertainty, fuzzy programming, M/M/c/K model, meta-heuristic algorithms

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1- Introduction

In today's highly dynamic and competitive supply chain environment, the efficient movement of goods is a cornerstone of economic success. The increasing complexity of logistics networks, characterized by diverse commodities, constrained capacities, and fluctuating demands, necessitates sophisticated optimization strategies. The multi-commodity routing problem (MCRP), a core challenge in logistics, involves transporting different types of goods through a network to meet the requirements of multiple destinations. The situation becomes significantly more complex when incorporating practical constraints such as limited capacities, variable transportation modes, and congestion in the network. This paper focuses on developing an optimization framework for the multi-commodity routing problem with added features of dynamic warehouse management, flexible vehicle ownership, and congestion control (Nozari & Aliahmadi, 2022).

The efficient routing of commodities requires a thorough understanding of the network's structure and constraints. Limited capacity is a critical challenge, affecting vehicles, warehouses, and transportation paths. Vehicles must be assigned to routes that maximize capacity utilization while adhering to delivery deadlines and minimizing costs. Similarly, warehouses act as critical nodes for storing and distributing goods, and their limited capacities can become bottlenecks in the system. A dynamic approach that allows for adding or removing warehouses based on current and projected demand offers significant flexibility and cost optimization opportunities (Najafi et al., 2022).

Another crucial dimension of this problem is the selection of appropriate transportation modes. Logistics systems often use a mix of owned and outsourced vehicles to address varying demand levels. Owned vehicles provide reliability and predictable costs but can be underutilized during periods of low demand. On the other hand, outsourced vehicles offer flexibility but typically come with higher variable costs. Striking the right balance between these two options is essential for achieving cost-effective and responsive supply chain operations (nozari et al., 2022).

Moreover, congestion is an increasingly pressing concern in logistics networks, particularly in urban and densely populated areas. Traffic bottlenecks and delays can significantly impact delivery times and operational costs. Effective congestion management requires routing and scheduling optimization to distribute traffic more evenly across the network and time periods. This involves selecting less congested routes and implementing scheduling strategies that reduce peak-hour demand on critical segments of the network (Nozari et al., 2021, Nozari & Szmelter-Jarosz, 2023).

The significance of addressing these interconnected challenges lies in the potential benefits for industries such as e-commerce, manufacturing, and urban logistics. In e-commerce, customer expectations for fast and reliable deliveries are constantly increasing, necessitating more agile and optimized logistics systems. Similarly, manufacturers rely on efficient supply chains to maintain production schedules and meet market demands (Nozari, 2024). Urban logistics, which involves last-mile deliveries, faces additional challenges like traffic congestion, environmental regulations, and limited urban infrastructure. Integrating dynamic warehouse management, diverse vehicle options, and congestion control into the multi-commodity routing problem provides a holistic solution to these pressing issues (Nozari, 2023).

Existing studies on the multi-commodity routing problem have focused on static models with fixed network capacities and vehicle options. While these models have provided valuable insights, they often fail to address modern supply chains' dynamic and real-world complexities. Incorporating dynamic elements such as adding or removing warehouses and adjusting vehicle ownership strategies represents a significant advancement in this field. Similarly, most existing models do not adequately account for congestion despite its critical impact on logistics performance. By integrating congestion management into the optimization framework, this study addresses a crucial gap in the literature.

The optimization model proposed in this paper aims to minimize total logistics costs while ensuring timely delivery and maintaining high service levels. The cost components considered include transportation costs (fixed and variable), warehouse operation costs, and congestion-related costs such as delays and fuel consumption. The model also incorporates constraints related to vehicle and warehouse capacities, delivery deadlines, and congestion thresholds. Advanced optimization techniques, such as mixed-integer programming and metaheuristic algorithms, are employed to solve the problem efficiently, even for large-scale networks.

This study makes three contributions. First, it develops a comprehensive optimization framework integrating dynamic warehouse management, vehicle ownership strategies, and congestion control into the multi-commodity routing problem. Second, it addresses practical constraints such as limited capacities and variable demands, providing a realistic and applicable solution for real-world logistics networks. Third, it demonstrates the effectiveness of the proposed model through numerical experiments and case studies, offering valuable insights for practitioners and policymakers in the field.

This study responds to the growing need for more agile, cost-effective, and sustainable logistics systems. Addressing the multi-commodity routing problem with the added dimensions of dynamic warehouse management, flexible vehicle ownership, and congestion control provides a novel and practical solution to a critical challenge in supply chain optimization. The findings of this study are expected to contribute to the advancement of logistics research and offer actionable strategies for improving supply chain performance in various industries.

2- Literature review

Due to its practical relevance and computational complexity, the multi-commodity routing problem (MCRP) has been a critical area of research in logistics and supply chain management. Over the years, numerous studies have explored MCRP from various perspectives, including routing optimization, capacity management, and network dynamics. This section reviews key contributions in multi-commodity routing, dynamic warehouse management, vehicle ownership strategies, and congestion control, highlighting their interconnections and identifying research gaps.

Multi-Commodity Routing Problems

MCRP involves determining optimal routes for transporting multiple commodities across a network to meet demand while minimizing costs and adhering to constraints. Early research in this field primarily focused on static problems with fixed network parameters. Magnanti and Wong (1984) provided a foundational overview of network flow models, including MCRP, and discussed various algorithms for solving such problems. Subsequent studies extended these models to incorporate more realistic constraints, such as vehicle capacities and delivery deadlines (Crainic & Laporte, 1997).

Recent advancements have emphasized dynamic and real-time routing. For instance, Holguín-Veras and Jaller (2014) investigated routing in time-dependent networks, where travel times vary based on traffic conditions. Their work demonstrated the importance of integrating temporal factors into routing decisions. However, many of these studies focus on single-commodity flows, leaving a gap in addressing the complexity of multi-commodity systems under dynamic conditions.

Dynamic Warehouse Management

Warehouses are pivotal in logistics networks, acting as storage and distribution hubs. Traditional models often assume fixed warehouse locations and capacities, limiting their applicability to real-world scenarios where demand fluctuations and operational constraints require dynamic adjustments. Liu et al. (2010) introduced models for facility location problems with dynamic capacities, emphasizing the cost benefits of adaptive warehouse management. Similarly, Shen and Qi (2007) examined the impact of opening and closing warehouses on supply chain performance, finding that dynamic strategies significantly improve cost efficiency.

Incorporating dynamic warehouse management into MCRP has gained traction in recent years. Govindan et al. (2017) proposed an integrated model combining routing optimization with facility location decisions, highlighting the interplay between transportation and storage costs. Nonetheless, these studies often overlook the operational complexities of managing warehouse additions or closures in congested networks, a gap this research aims to address.

Vehicle Ownership and Fleet Management

Vehicle ownership strategies are critical in logistics, balancing cost efficiency and operational flexibility. Fixed fleets of owned vehicles offer cost predictability but can result in underutilization during low-demand periods. In contrast, outsourcing provides flexibility but incurs higher per-unit costs. Studies such as those by Cordeau et al. (2001) have analyzed vehicle routing problems (VRP) with mixed fleets, offering insights into the trade-offs between ownership and outsourcing.

Advanced VRP models have incorporated additional dimensions, such as vehicle heterogeneity and time windows. Kuo and Wang (2011) explored the benefits of using a combination of vehicle types to optimize routing and capacity utilization. However, these models typically focus on single-commodity flows or static networks, limiting their applicability to dynamic, multi-commodity scenarios. This paper extends these concepts by integrating vehicle ownership decisions into a multi-commodity routing framework with dynamic warehouse and congestion considerations.

Congestion Management in Logistics

Congestion is a growing challenge in logistics, particularly in urban environments where traffic delays can significantly impact delivery schedules and costs. Research in this area has focused on developing congestion-aware routing models that optimize travel times and reduce bottlenecks. Boyles and Waller (2011) proposed a framework for modeling congestion in transportation networks, emphasizing the need for demand management and dynamic routing. Similarly, Nagurney et al. (2002) introduced user-equilibrium models to account for traffic congestion in network design.

Despite these advancements, most congestion-focused studies address single-commodity flows or assume static network parameters. The integration of congestion management into multi-commodity routing problems remains underexplored. This study builds on prior research by incorporating real-time congestion data into a dynamic optimization framework, enabling more efficient routing and scheduling decisions.

Integrated Approaches to MCRP

Integrating multiple dimensions, such as dynamic warehouse management, vehicle ownership strategies, and congestion control, into MCRP has received limited attention. Existing studies focus on one or two aspects in isolation, overlooking their interdependencies. For instance, Lin et al. (2014) developed a hybrid model combining facility location and vehicle routing but did not account for congestion. Similarly, Goel and Vidal (2014) explored mixed fleet management in dynamic networks but did not consider warehouse adjustments.

Recent research has highlighted the benefits of integrated approaches. Chen et al. (2016) proposed a comprehensive model for supply chain optimization, combining routing, inventory management, and congestion control. Their findings demonstrated significant cost savings and service level improvements but were limited to single-commodity systems. This paper addresses these limitations by presenting a holistic optimization framework for multi-commodity routing with dynamic warehouse and fleet management under congestion.

Research Gaps and Contributions

While considerable progress has been made in these areas, significant gaps remain in the literature. Most existing studies:

1. Address static or single-commodity routing problems, limiting their applicability to dynamic, multi-commodity scenarios.
2. Focus on isolated aspects, such as routing or facility location, without considering interdependencies.
3. Do not adequately integrate congestion management into logistics optimization frameworks.

This study contributes to the literature by:

- Developing an integrated optimization model for MCRP that combines dynamic warehouse management, vehicle ownership strategies, and congestion control.

- Addressing practical constraints, such as limited capacities and fluctuating demands, to enhance the model's real-world applicability.
- Demonstrating the effectiveness of the proposed framework through numerical experiments and case studies, providing actionable insights for logistics practitioners and policymakers.

In summary, this paper builds on existing research in MCRP, dynamic facility management, fleet optimization, and congestion control, offering a novel and comprehensive solution to a critical logistics challenge.

3- Modeling

3-1 Mathematical Problem

The research methodology for optimizing the multi-commodity routing problem (MCRP) in this study leverages **multi-objective optimization techniques**, specifically the **Multi-Objective Grey Wolf Optimizer (MOGWO)** and the **Non-Dominated Sorting Genetic Algorithm II (NSGA-II)**. These algorithms address the problem's complexities, including multiple conflicting objectives, dynamic warehouse management, vehicle ownership strategies, and congestion management.

This research presents a multi-item location-routing model of limited capacity in which strategic and tactical goals are adopted simultaneously. In this mathematical model and in Figure 1, there is a set of suppliers, warehouses, and customers, the purpose of which is to supply customers' non-deterministic demand by vehicle routing.

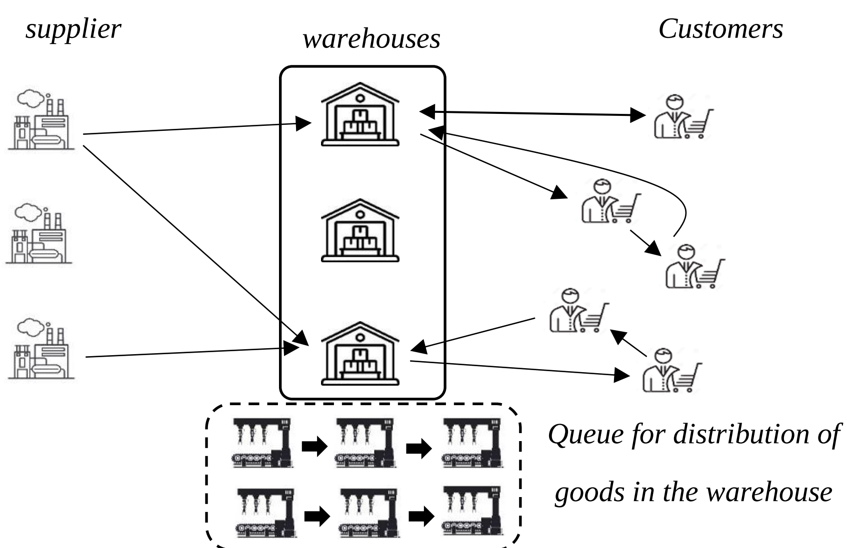

Figure 1: Schematic of the location-routing problem

In this model, warehouses, after locating, store, and distribute different items to customers through other vehicles. In each period, various sets of cars leave each warehouse and return to the warehouse after visiting a set of customers. The supply of items needed by warehouses is also done through different vehicles and by suppliers. Therefore, in this mathematical model, strategic decisions, such as selecting suppliers and warehouses, and tactical decisions, such as vehicle routing for product distribution, the amount of inventory stored at the end of each period, and route allocation between suppliers and warehouses are adopted. On the other hand, a soft time window is also considered in the mathematical model so that every customer can receive his goods in that time window. Exceeding the time window by the vehicle will result in a penalty in the cost objective function. Also, each warehouse has several servers with different service rates (exponential distribution) based on the volume of incoming products and customer demand, according to capacity level.

The symbols used in the mathematical model include the set, parameters and decision variables as follows:

Sets

I	The set of suppliers $i \in \{1,2,\dots,I\}$
J	The set of warehouses $j \in \{1,2,\dots,J\}$
K	set of customers $k \in \{1,2,\dots,K\}$
V	Set of vehicles $v \in \{1,2,\dots,V\}$
T	The set of time periods $t \in \{1,2,\dots,T\}$
P	The set of products $p \in \{1,2,\dots,P\}$

Parameters

e_j	Fixed cost of warehouse selection at location j∈J
u_i	Fixed cost of supplier selection at location i∈I
c_j	Cost of distribution of products from warehouse j∈J
f_v	Fixed cost (rental or salary) of using vehicle v∈V
$\widetilde{tr}_{ijv}$	Transportation cost of each product unit by vehicle v∈V between supplier i∈I and warehouse j∈J
$\widetilde{tr}_{jkv}$	The cost of transporting each product unit by vehicle v∈V between node j∈{J∪K} and node k∈{J∪K}
h_j	The cost of keeping each unit of product in warehouse j∈J
π	Penalty fee for exceeding the time window
t'_{jkv}	Time to transfer products by vehicle v∈V between node j∈{J∪K} and node k∈{J∪K}
t'_{ijv}	Time of transportation of products by vehicle v∈V between supplier i∈I and warehouse j∈J
r_{jkv}	Risk of transporting products by vehicle v∈V between node j∈{J∪K} and node k∈{J∪K}
r_{ijv}	Risk of transporting products by vehicle v∈V between supplier i∈I and warehouse j∈J
t''_k	The time of unloading and loading products at customer k∈K
$[a_k, b_k]$	Delivery time window of customer products k∈K
$\tilde{d}_{kpt}$	Customer demand k∈K of product p∈P in time period t∈T
ca_{jp}	Maximum distribution capacity of products from warehouse j∈J of product p∈P
ca_{ip}	The maximum capacity of supplier i∈I of product p∈P
ca_{vp}	Vehicle capacity v∈V from product p∈P
μ_j	Service rate of warehouse j∈J (exponential distribution)
B_{jt}	The upper limit of the queue length for serving at warehouse j∈J in the time period t∈T

θ_{jt}	The upper limit probability for the excessive service queue length at warehouse j∈J in the time period t∈T
ϑ	Number of servers in each warehouse

Decision Variables

Y_{ijpvt}	Product transfer volume p∈P between supplier i∈I and warehouse j∈J by vehicle v∈V in time period t∈T
V_{jpt}	Total volume of product p∈P transferred from warehouse j∈J in time period t∈J
Q_{jpr}	Inventory amount of product p∈P in warehouse j∈J at the end of time period t∈T
Z_j	If the warehouse is selected in location j∈J, it takes the value 1 and otherwise 0.
W_i	If the supplier is selected in location i∈I, it takes the value 1 and otherwise 0.
A_{vt}	If the vehicle v∈V is used in the time period t∈T, it takes the value 1 and otherwise 0.
I_{jkt}	If the customer k∈K is assigned to the warehouse j∈J in the time period t∈T, it takes the value 1 and otherwise 0.
X_{jkvt}	If the customer k∈K is visited after the warehouse j∈J by the vehicle v∈J in the time period t∈J, it takes the value 1 and otherwise 0. k,j∈J∪K
U_{kvt}	Auxiliary variable for sub-tour deletion constraint
D_{jkvt}	Arrival time of vehicle v∈V assigned to warehouse j∈J in visiting customer k∈K in time period t∈T
DT_{kvt}	The amount of exceeding the time window in the arrival of the vehicle v∈V to the customer k∈K in the time period t∈T
S_{ijvt}	If the vehicle v∈V travels between the supplier i∈I and the warehouse j∈J in the time period t∈T, it takes the value 1 and otherwise 0.
λ_{jt}	Customer arrival rate to warehouse j∈J in time period t∈T
π_{0jt}	The probability of the construction of warehouse j∈J in the time period t∈T
W_{jt}	Customer waiting time in warehouse j∈J in time period t∈T

According to the presented symbols, the three-objective problem of multi-commodity location-routing of limited capacity with the ability to remove and add warehouse and different types of vehicles in terms of ownership with congestion management: the M/M/c/K queue model is modeled as follows:

$$\begin{aligned} Min\ Cost = & \sum_{j=1}^{J} e_j Z_j + \sum_{i=1}^{I} u_i W_i + \sum_{v=1}^{V}\sum_{t=1}^{T} f_v A_{vt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{t=1}^{T} f_v S_{ijvt} \\ & + \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} h_j Q_{jpt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} \widetilde{tr}_{ijv} Y_{ijpvt} \\ & + \sum_{j=1}^{J\cup K}\sum_{k=1}^{J\cup K}\sum_{p=1}^{P}\sum_{v=1}^{V}\sum_{t=1}^{T} \widetilde{tr}_{jkv} \tilde{d}_{kpt} X_{jkvt} + \sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T} c_j V_{jpt} \\ & + \sum_{k=1}^{K}\sum_{v=1}^{V}\sum_{t=1}^{T} \pi DT_{kvt} \end{aligned} \tag{1}$$

$$Min\ Time = \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{v=1}^{V}\sum_{t=1}^{T} D_{jkvt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{t=1}^{T} t'_{ijv} S_{ijvt} \tag{2}$$

$$Min\ Risk = \sum_{j=1}^{J\cup K}\sum_{k=1}^{J\cup K}\sum_{v=1}^{V}\sum_{t=1}^{T} r_{jkv}X_{jkvt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{t=1}^{T} r_{ijv}S_{ijvt} \tag{3}$$

$s.t$:

$$\sum_{v=1}^{V}\sum_{j=1}^{K\cup J} X_{jkvt} = 1, \quad \forall k \in K, t \in T \tag{4}$$

$$\sum_{k=1}^{K\cup J} X_{jkvt} = \sum_{k=1}^{K\cup J} X_{kjvt}, \quad \forall j \in K \cup J, v \in V, t \in T \tag{5}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K} X_{jkvt} \leq 1, \quad \forall v \in V, t \in T \tag{6}$$

$$-I_{jkt} + \sum_{u=1}^{J\cup K}\left(X_{juvt} + X_{ukvt}\right) \leq 1, \quad \forall j \in J, k \in K, v \in V, t \in T \tag{7}$$

$$U_{k'vt} - U_{kvt} + |K|X_{k'kvt} \leq |K| - 1, \quad \forall k', k \in K, v \in V, t \in T \tag{8}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{K\cup J} \tilde{d}_{kpt}X_{jkvt} \leq ca_{vp}A_{vt}, \quad \forall p \in P, v \in V, t \in T \tag{9}$$

$$V_{jpt} + Q_{jp,t-1} = Q_{jpt} + \sum_{k=1}^{K}\sum_{v=1}^{V} \tilde{d}_{kpt}I_{jkt}, \quad \forall j \in J, p \in P, t \in T \tag{10}$$

$$V_{jpt} \leq \sum_{p=1}^{P} ca_{jp}\, Z_j, \quad \forall j \in J, t \in T \tag{11}$$

$$D_{jkvt} \geq t'_{jkv} - M\left(1 - X_{jkvt}\right), \quad \forall\, j \in J, k \in K, v \in V, t \in T \tag{12}$$

$$D_{jk'vt} \geq D_{jkvt} + t''_{k} + t'_{kk'v} - M\left(2 - X_{kk'vt} - I_{jkt}\right), \quad \forall\, j \in J, k, k' \in K, v \in V, t \in T \tag{13}$$

$$a_k X_{jkvt} - D_{jkvt} \leq DT_{kvt} \leq D_{jkvt} - b_k X_{jkvt}, \quad \forall\, j \in J, k \in K, v \in V, t \in T \tag{14}$$

$$\sum_{i=1}^{I}\sum_{v=1}^{V} Y_{ijpvt} = V_{jpt}, \quad \forall j \in J, p \in P, t \in T \tag{15}$$

$$Y_{ijpvt} \leq ca_{vp}S_{ijvt}, \quad \forall\, i \in I, j \in J, p \in P, v \in V, t \in T \tag{16}$$

$$\sum_{j=1}^{J}\sum_{v=1}^{V} Y_{ijpvt} \leq ca_{ip}W_i, \quad \forall i \in I, p \in P, t \in T \tag{17}$$

$$P\left\{j\ Warehouse\ in\ long\ line\ distribution\ products > B_{jt}\right\} \leq \theta_{jt}, \quad \forall j \in J, t \in T \tag{18}$$

$$Y_{ijpvt}, V_{jpt}, Q_{jpr}, U_{kvt}, D_{jkvt}, DT_{kvt}, \lambda_{jt}, \pi_{0jt}, W_{jt} \geq 0 \tag{19}$$

$$Z_j, W_i, A_{vt}, I_{jkt}, X_{jkvt}, S_{ijvt} \in \{0,1\} \tag{20}$$

Equation (1) shows the first objective function of the problem, which involves minimizing the total cost of routing. In this function, the cost objective includes, respectively, the costs of locating and selecting suppliers, warehouses, the costs of using different vehicles, the cost of maintaining inventory, transportation costs, the operational cost of product distribution, and the cost of fines in case of exceeding the time window. Equation (2) shows the second objective function of the problem, which includes minimizing the total time of supplying and distributing products to customers. Equation (3) minimizes the total risk of transporting products by different vehicles under the third objective function. Equation (4) shows that each warehouse should be assigned to only one customer. Equation (35) shows that every vehicle entering a customer node must leave it. The relation (6) shows that each maximum effect customer should be visited by one vehicle. Relation (7) guarantees that every vehicle must return to the warehouse after visiting customers. Equation (8) shows the equation related to sub-tour elimination. Equation (9) shows that the maximum capacity of the vehicle can be used to transport products. Equation (10) calculates the amount of inventory at the end of the time period in each warehouse. Equation (11) shows that if a warehouse is selected and located, its maximum capacity can be used. Equations (12) and (13) show the time of the vehicle reaching the first customer and the next customers. Equation (14) calculates the amount of time exceeding the time window. Equation (15) shows the amount of product transferred between suppliers and warehouses. Equation (16) shows the type of vehicle allocated to distribute items between suppliers and warehouses. Equation (17) shows that if a supplier is selected and located, its maximum capacity can be used. Equation (18) shows that the probability of queue length in each warehouse should not exceed the acceptable limit. Relations (19) and (20) show the type of decision variables of the problem.

3-2 Multi-Objective Grey Wolf Optimizer (MOGWO) Algorithm

The **Multi-Objective Grey Wolf Optimizer (MOGWO)** is an evolutionary algorithm inspired by the hunting behavior and leadership hierarchy of grey wolves in nature. It is particularly suited for solving multi-objective optimization problems (MOOPs) due to its ability to maintain a balance between exploration (searching new areas of the solution space) and exploitation (refining known good solutions). The algorithm employs a pack of grey wolves, each representing a candidate solution, to converge toward a set of optimal trade-offs, forming the Pareto front.

Key Features of MOGWO

1. **Leadership Hierarchy**:
   - Alpha (α): The best solution.
   - Beta (β) and Delta (δ): The second and third best solutions.
   - Omega (ω): The remaining population, guided by α, β, and δ.
2. **Social Behavior**:
   - Wolves update their positions based on the guidance of the top leaders.
3. **Non-Dominated Sorting**:
   - Solutions are ranked into Pareto fronts, maintaining a diverse, high-quality set of solutions.

1. Initialize the grey wolf population with random solutions.

2. Define the number of objectives and constraints.

3. Evaluate the fitness of each wolf based on the objectives.

4. Identify the alpha, beta, and delta wolves.

5. While stopping criteria not met:

a. For each wolf in the population:

i. Update its position using:

- Positions of alpha, beta, and delta.

- Adaptive coefficients to control exploration and exploitation.

b. Evaluate the fitness of the updated positions.

c. Perform non-dominated sorting to rank solutions into Pareto fronts.

d. Use crowding distance to maintain diversity within the Pareto fronts.

6. Return the Pareto front as the set of optimal solutions.

Figure 2: Pseudocode of MOGWO algorithm

Figure 3 is a schematic representation of the MOGWO algorithm's workflow:

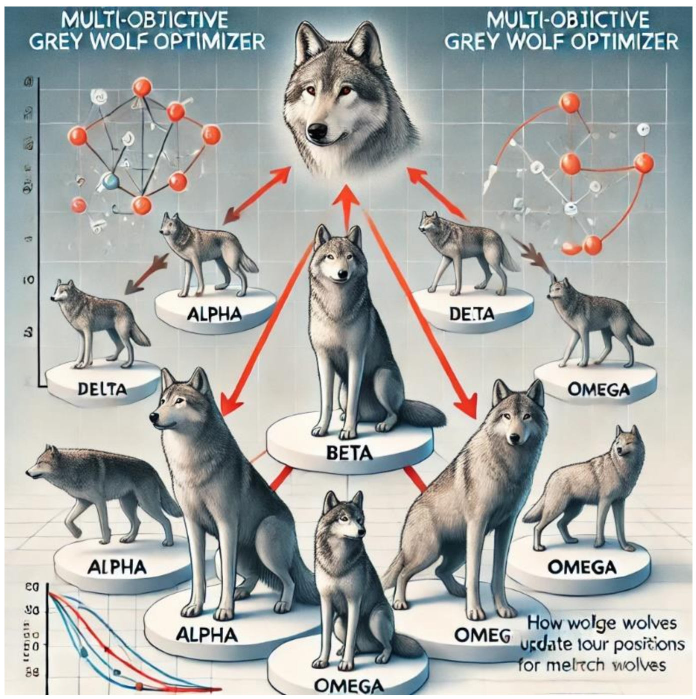

Figure 3: Schematic of MOGWO algorithm

The image illustrates the key steps of the Multi-Objective Grey Wolf Optimizer (MOGWO) algorithm, showcasing the hierarchical structure of wolves (α\alpha, β\beta, δ\delta, and ω\omega) and how they coordinate to update positions and converge toward the optimal solutions. The process of maintaining a Pareto front for multi-objective optimization is also highlighted.

3-3 Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

The **Non-Dominated Sorting Genetic Algorithm II (NSGA-II)** is a widely used evolutionary algorithm for solving multi-objective optimization problems (MOOPs). It efficiently identifies a diverse set of Pareto-optimal solutions, balancing conflicting objectives. NSGA-II's strength lies in its use of **fast non-dominated sorting** and a **crowding distance mechanism** to maintain solution diversity.

1. Initialize the population with random solutions.

2. Evaluate the fitness of each solution for all objectives.

3. Perform non-dominated sorting to classify solutions into Pareto fronts.

4. While stopping criteria not met:

a. Perform selection using tournament selection based on rank and crowding distance.

b. Apply crossover and mutation operators to generate offspring.

c. Combine parent and offspring populations.

d. Perform non-dominated sorting on the combined population.

e. Select the top N solutions for the next generation using rank and crowding distance.

5. Return the Pareto front as the set of optimal solutions.

Figure 4: Pseudocode of **NSGA-II** algorithm

Figure 5 is a schematic representation of the NSGA-II algorithm's workflow, showing the processes of non-dominated sorting, crowding distance, selection, and elitism.

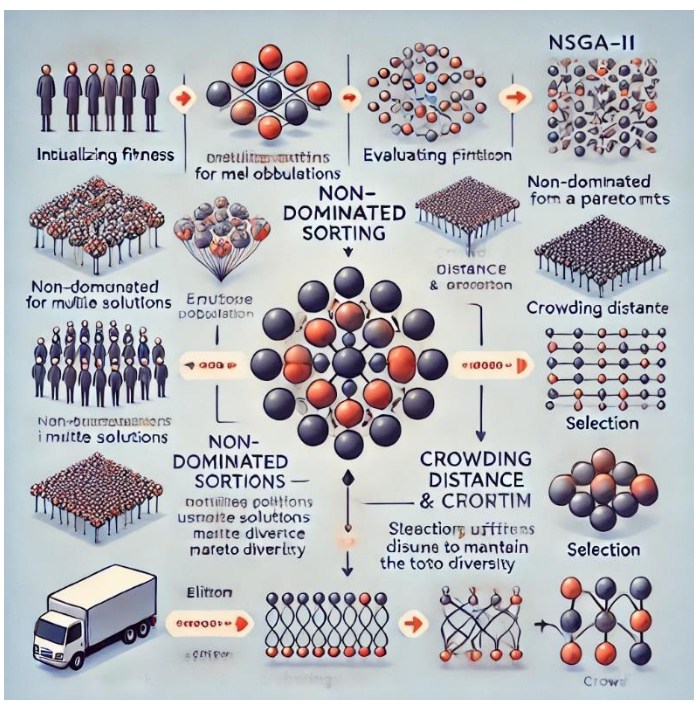

Figure 4: Schematic of **NSGA-II** algorithm

The image provides a detailed depiction of the NSGA-II algorithm, highlighting the key steps such as non-dominated sorting, crowding distance computation, selection, crossover, mutation, and elitism. These steps collectively ensure the identification of a diverse set of optimal trade-off solutions for multi-objective problems.

4- Research finding

In this research, considering the complexities of the model in terms of the number of parameters and variables and the capabilities of GAMS in solving planning models, this software was chosen to solve and analyze the numerical results. The problems are also run on a laptop with Intel Core i7 specifications, (8GB RAM) by GAMS software and BARON solver. To evaluate the presented model, the data received from the studied company has been used, and the inputs considered in the model are as follows:

To validate the mathematical model, the sets considered in the model are described in Table 1:

Table 1: Numerical example size

Size	**Description**
4	customer
3	warehouse
3	supplier
4	Vehicle
2	time period
2	product

Due to the indeterminacy of some parameters of the problem, in order to use the fuzzy programming method in the control of the mathematical model, an uncertainty rate of 0.5 has been considered.

The Paypff table obtained from solving the numerical example is shown in Table 2. In the Paypff table, the obtained values are the achievement of the optimal value of each objective function without considering other objective functions. This table shows the best and worst values of each objective function.

Table 2: Payoff table, numerical example of small size

	OF1	OF2	OF3
OF1	32759.51	265.79	67.11
OF2	83817.40	160.03	51.25
OF3	82540.63	249.80	47.48

Table 2 shows that the best value of the cost objective function is equal to $32759.51. In this case, the total distribution time obtained was equal to 265.79 minutes and the transfer risk was equal to 67.11. When the goal is to optimize the distribution time, the best value of the second objective function is equal to 160.03 minutes. In this case, the total cost is 83817.40 dollars and the total risk of product transfer is 51.25. On the other hand, when the goal is to optimize the total risk of product transfer, this value is equal to 47.48. In this case, the total location-routing costs are $82,540.63 and the total distribution time is 249.80 minutes.

After obtaining the Payoff table, the set of efficient solutions obtained from the epsilon constraint method is shown in Table 3.

Table 3: The set of effective solutions of the numerical example

Best Solution	OF1	OF2	OF3
1	32759.51	265.79	67.11
2	33025.93	246.55	53.316
3	33300.73	242.93	52.44
4	33659.17	229.96	52.01
5	33929.12	223.2	51.91
6	34456.12	199.58	50.81
7	35834.59	199.24	49.92

The results of Table 3 show that with the reduction of the total transfer time, due to the use of vehicles with higher speed and cost, the total location-routing costs have increased. Also, by reducing the risk of transferring products, the total costs have increased.

5- Conclusion

This research focuses on optimizing the multi-commodity routing problem (MCRP) with limited capacity, dynamic warehouse management, diverse vehicle ownership models, and congestion considerations. Leveraging advanced mathematical modeling and multi-objective optimization techniques, including the **Multi-Objective Grey Wolf Optimizer (MOGWO)** and the **Non-Dominated Sorting Genetic Algorithm II (NSGA-II)**, the study successfully addresses the inherent complexities of modern logistics networks.

Including dynamic constraints, such as the ability to open or close warehouses and congestion management, adds real-world applicability to the model. This dynamic aspect allows logistics managers to adapt to fluctuating demands and operational challenges, leading to cost-effective and efficient supply chain operations. The research framework optimizes transportation costs, warehouse operational costs, and congestion-related delays. This multi-faceted approach ensures that the solution balances economic efficiency, service quality, and sustainability.

This study bridges the gap between theoretical optimization models and practical logistics applications.

- **Dynamic Warehouse Management**: Adding or removing warehouses based on operational needs can significantly reduce fixed costs and improve service levels.
- **Vehicle Ownership Decisions**: By incorporating both owned and outsourced vehicle models, the research provides actionable strategies for fleet management, allowing organizations to optimize resource utilization and cost efficiency.

- **Congestion Management**: Considering congestion in routing decisions leads to more realistic and applicable solutions, especially in urban and high-traffic environments.

These findings are valuable for the e-commerce, retail, and manufacturing industries, where multi-commodity routing is critical to supply chain performance.

This research contributes significantly to logistics optimization by addressing a critical real-world problem with innovative methodologies. The use of advanced algorithms to tackle multi-objective routing problems demonstrates the potential of artificial intelligence and optimization techniques in transforming supply chain management. The insights gained from this study provide a foundation for developing adaptive, cost-effective, and sustainable logistics solutions, marking an important step toward smarter and more efficient supply chain operations.

Reference

Boyles, S. D., & Waller, S. T. (2011). A mean-variance model for the minimum cost network flow problem with random arc costs. Transportation Research Part B: Methodological, 45(5), 837-860.

Chen, Y., Govindan, K., & Yang, Z. (2016). Robust optimization for multiperiod closed-loop supply chain network design under uncertainty. Transportation Research Part E: Logistics and Transportation Review, 89, 28-52.

Cordeau, J.-F., Laporte, G., Savelsbergh, M. W., & Vigo, D. (2007). Vehicle routing. In Transportation (pp. 367-428). Springer.

Crainic, T. G., & Laporte, G. (1997). Planning models for freight transportation. European Journal of Operational Research, 97(3), 409-438.

Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. European Journal of Operational Research, 263(1), 108-141.

Holguín-Veras, J., & Jaller, M. (2014). Freight demand management and the potential of receiver-led consolidation programs. Transportation Research Part A: Policy and Practice, 66, 109-124.

Kuo, Y., & Wang, C. C. (2011). Optimizing the VRP by minimizing energy consumption. Computers & Industrial Engineering, 62(2), 364-372.

Liu, W., Wang, J., & Huang, Y. (2010). Dynamic facility location problem with time-varying demand and intermittent disruptions. Transportation Research Part B: Methodological, 44(6), 798-827.

Magnanti, T. L., & Wong, R. T. (1984). Network design and transportation planning: Models and algorithms. Transportation Science, 18(1), 1-55.

Najafi, S. E., Nozari, H., & Edalatpanah, S. A. (2022). Artificial Intelligence of Things (AIoT) and Industry 4.0–Based Supply Chain (FMCG Industry). A Roadmap for Enabling Industry 4.0 by Artificial Intelligence, 31-41.

Nozari, H. (2024). Investigating Key Dimensions and Key Indicators of AIoT-Based Supply Chain in Sustainable Business Development. In Artificial Intelligence of Things for Achieving Sustainable Development Goals (pp. 293-310). Cham: Springer Nature Switzerland.

Nozari, H. (Ed.). (2023). Building Smart and Sustainable Businesses with Transformative Technologies. IGI Global.

Nozari, H., & Aliahmadi, A. (2022). Lean supply chain based on IoT and blockchain: Quantitative analysis of critical success factors (CSF). Journal of Industrial and Systems Engineering, 14(3), 149-167.

Nozari, H., & Szmelter-Jarosz, A. (2024). An Analytical Framework for Smart Supply Chains 5.0. In Building Smart and Sustainable Businesses With Transformative Technologies (pp. 1-15). IGI Global.

Nozari, H., Fallah, M., & Szmelter-Jarosz, A. (2021). A conceptual framework of green smart IoT-based supply chain management. International journal of research in industrial engineering, 10(1), 22-34.

Nozari, H., Ghahremani-Nahr, J., Fallah, M., & Szmelter-Jarosz, A. (2022). Assessment of cyber risks in an IoT-based supply chain using a fuzzy decision-making method. International Journal of Innovation in Management, Economics and Social Sciences, 2(1).

Shen, Z.-J. M., & Qi, L. (2007). Incorporating inventory and routing costs in strategic location models. European Journal of Operational Research, 179(2), 372-389.