MJFAS
Malaysian Journal of Fundamental and Applied Sciences

Almadani and Aziz | Malaysian Journal of Fundamental and Applied Sciences, Vol. 20 (2024) 1261-1273

RESEARCH ARTICLE

Modelling a Dual-Objective Optimization Model for Cost Reduction and Disruption Risk Minimization in Automotive Supply Chains

Khalid Solaman Almadani[a], Nur Arina Bazilah Aziz[a,b*]

[a]Department of Mathematical Sciences, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia; [b]UTM-Centre for Industrial and Applied Mathematics, Ibnu Sina Institute for Scientific and Industrial Research, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

Abstract Dual-Objective Optimization model is vital in automotive supply chains (ASC) to emphasize multi-modal transportation under disruption scenarios at minimizing costs and disruption risks. In this context, the study evaluated the hypothetical and real-world data based on the deployment of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to understand the efficacy of incorporating multi-modal transportation to balance cost reduction and risk mitigation. The findings of Dual-Objective Optimization model revealed the model's superiority in identifying cost-effective transportation modes, offering a significant improvement over previous model. This research contributes to the mathematical modelling by providing a comprehensive framework for automotive supply chains, addressing operational efficiency and resilience against disruptions.

Keywords: Dual-objective optimization, automotive supply chains, (NSGA-II), multi-modal transportation, disruption risks.

Introduction

In the complex world of automotive supply chain management, managing frequent and complicated disruptions presents a growing challenge to optimizing profitability and minimizing costs. Operational stability, financial health, and market competitiveness are all significantly affected by disruption risk. Production can be disrupted and risks such as technological changes, supplier failures, and natural disasters can erode customer trust. It is necessary to effectively manage these risks to ensure the automotive supply chain's sustained success and resilience. This study builds upon foundational work by [1] by integrating economic factors into supply chain modeling. They revealed that the industry's primary issue is the frequent termination of commercial relationships between suppliers and distributors, which is often caused by external factors such as natural disasters, man-made incidents, and production line disruptions. These challenges not only impede trust-based relationships between suppliers and customers, but they also have a significant impact on the financial and operational stability of supply chains.

In this regard, optimizing a model to perform and address such challenges using the lens of multi-objective optimization (MOO), associated with the specific focus on multi-modal networks under disruption risk, is important in the automotive supply chain [2]. Pushpamali *et al*. [3] acknowledge the significance of integrating economic, environmental, and social factors into supply chain modeling. Several researchers [4-7] have contributed to recent literature, demonstrating the escalating need for resilient supply chain strategies. These studies revealed a growing inclination towards MOO for addressing the challenges in automotive supply chains, particularly emphasizing the need for resilience strategies such as resource allocation and business continuity planning [8].

On the other hand, the novel approach proposed by [9] was demonstrated by the foraging behaviour of natural Physarum, highlighting the potential of artificial intelligence (AI)-driven tools in improving the

***For correspondence:**
nurarina@utm.my

Received: 25 April 2024
Accepted: 16 Oct. 2024

robustness of logistics networks. Artificial intelligence (AI)-driven tools have a tremendous deal of potential to strengthen logistics networks [10] as it can dynamically analyzes large datasets to forecast disruptions, improve routing and inventory control, and suggest the most reliable and affordable transportation modes [11]. The incorporation of artificial intelligence (AI) into multimodal transportation systems can enhance supply chains' flexibility, effectiveness, and ability to resist disruptions [12].

This study aims to develop a dual-objective mathematical model that integrates the minimization of supply chain costs and disruption risk reduction. It implements the Non-dominated Sorting Genetic Algorithm II (NSGA-II), utilizing iterative genetic operations to efficiently enhance decision-making. This approach sorts of solutions into levels of non-domination, forming a Pareto front that facilitates optimal trade-offs between costs and risks. From the results, the research will formulate strategies to significantly reduce supply chain costs and improve disruption risk management.

Literature Review

The contemporary automotive supply chain is a complex network that extends beyond the physical flow of goods, encompassing information and financial flows. This complexity necessitates the integration of economic, environmental, and social considerations into supply chain decisions [3]. To enhance the operational efficient, the automotive supply chain management sector must undergo major evolution which is propelled by the urgent need to consider objectives such as: minimizing the total cost and reducing the risks of disruption. Our research extends existing knowledge by focusing on a dual-objective optimization model that integrates both supply chain cost minimization and disruption risk reduction, with a special emphasis on multi-modal transportation networks as we recognize their critical role in reducing costs and mitigating risks associated with supply chain disruptions.

Silva *et al*. [13] highlight the importance of integrating safety stock and safety time decisions in multi-supplier, multi-item industrial supply chains. Their decision support system (DSS) optimizes upstream inventory holding costs and service levels, underscoring the relevance of multi-objective approaches in dynamic and uncertain supply chain environments.

Mohebban-Azad *et al*. [1], presents a robust optimization approach for designing a reliable multi-level, multi-product, and multi-period location-inventory-routing three-echelon supply chain network that considers disruption risks and uncertainty in the inventory system. Unlike our study, which integrates multi-modal transportation strategies to minimize overall supply chain costs and disruption risks, the article focuses on a mixed-integer nonlinear programming multi-objective model without explicitly addressing multi-modal transportation options.

The model presented by [1] shares similarities with our study in addressing supply chain optimization. However, their approach does not incorporate the multi-modal transportation network strategy that characterizes our model. This distinction highlights our contribution in exploring transportation mode flexibility to enhance supply chain resilience and efficiency, a dimension not developed in their research.

Almasi [14] develops a multi-objective mathematical model for sustainable supplier selection and order allocation, incorporating risk and inflation considerations. This approach is closely related to our research's objective of optimizing supplier selection and transportation mode decisions under uncertain conditions.

Feng and Gong [15] introduce an integrated model combining linguistic entropy weight method (LEWM) with multi-objective programming for green supplier selection and order allocation. Their framework, which aims to minimize total cost, carbon emissions, and maximize procurement value, provides insights into the potential of multi-objective optimization in enhancing green supply chain management practices in the automotive industry.

Methodology

This research integrates the strengths of dual-objective optimization for cost reduction and disruption risk minimization with the sophisticated capabilities of the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The focus in the methodology is on selecting the optimal multi-modal network, tailored to withstand disruption risks in the automotive supply chain. By employing NSGA-II, our model navigates through the complexities of various transportation modes, enabling decision-makers to effectively balance cost efficiency with robust disruption risk management. This strategic solution addresses the dynamic challenges and uncertainties prevalent in the automotive industry's supply chain networks. Figure 1 shows the conceptual framework for MOO in ASC for a visual representation of the methodology's foundation.

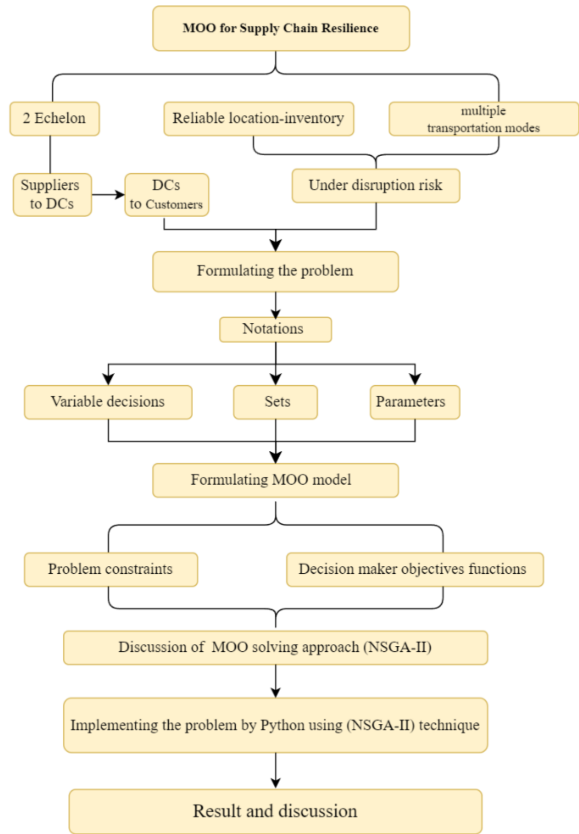

Figure 1. The conceptual framework for MOO in ASC

Supply Chain Network Design Based on Developed Model

This study has used three supply chain factors in terms of design, such as network structure, focus on reliable location inventory, and multi-modal transportation, as shown in Figure 2.

(a) Network Structure: The study employs a two-echelon supply chain network, encompassing suppliers, distribution centers, and customers.
(b) Focus on Reliable Location Inventory: Emphasizing the importance of strategic inventory placement and management.
(c) Multi-modal Transportation: Considering the risks associated with different transportation modes under potential disruptions.

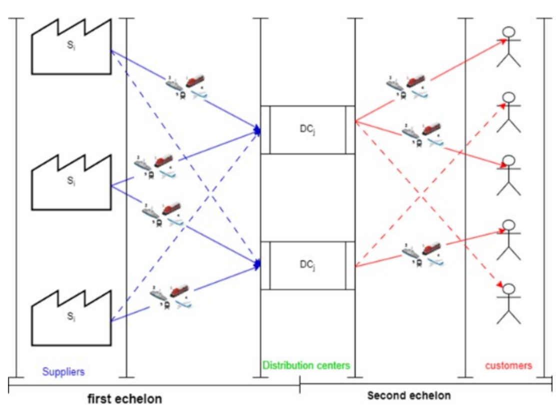

Figure 2. Structure of supply chain problem

Optimization Model Development

Herewith, the detailed formulation of sets, parameters, and variables relevant to the automotive supply chain regarding define problem notation have been mentioned in Tables 1, 2, and 3.

Table 1. Sets in formulation of the model

	Sets
A	Customers
J	Distribution centres (DC)
I	Suppliers
L_m	Transportation modes, m=1,2,3,4
G	Products
T	Periods
K	Service levels
F	available facilities
NF	Non-available facilities

Table 2. Parameters in formulation of the model

	Description
NL_{lt}:	Number of visits by each type of transportation l in period t
θ^k:	The likelihood of DC disruption in service level k
β_{it}:	The likelihood of supplier disruption i in period t
cL_l:	Capacity of transportation mode l
fL_l:	Fixed cost for using transportation mode l
Cn_{au}:	Transportation cost between nodes
Cs_{jt}:	Cost of scarcity for DC j in period t
fo_{jt}:	Fixed cost of opening DC j in period t
$Csh1_{ja}$:	Cost of shipping from DC j to customer a
$Csh2_{ijtg}$:	Cost of shipping from supplier i to DC j for product g in period t
Ch_{jtg}:	Cost of holding in DC j for product g in period t
w_{ajtg}:	Customer a demand for product g from DC j in period t;
gr_{jg}	Product g price for DC j
Nv_{jg}:	Initial Inventory of DC j for product g
fE_{jt}:	Fixed cost for employing the additional capacity of DC j in period t
OB_j:	The overall budget of DC j
ax_j:	The additional capacity of DC j
tx_j:	The typical capacity of DC j
C_{lg}:	Cost of transporting product g using transportation mode l

Where C_{lg} is a new parameter Introduced to provide a detailed cost metric for transporting product g using mode l, enhancing the model's ability to perform fine-grained cost analysis and comparison across different transportation modes.

Table 3. Variables in formulation of the model

Variables	Description
Y_{ijtg}:	1 if product g was assigned to DC j by supplier i during period t, 0 otherwise
X_{jagk}:	1 If DC j received customer a for product g at service level k, 0 otherwise
K_{jalkt}:	1 if shipping mode l in period t at service level k connects a to j, 0 otherwise
S_{jtg}:	1 if the product g is subject to a scarcity in j during the time t, 0 otherwise
AS_{jtg}:	1 if additional capacity is needed in DC j for product g during period t, 0 otherwise
N_{ijtg}:	Order quantity of DC j for product g in period t from supplier i
NG_{jagt}:	Number of products g that is shipped from DC j to customer a during t
NS_{jtg}:	Number of shortages allowing for Product g in Period t in DC j
NAS_{jtg}:	Number of additional capacity use from product g in period t in DC j
HV_{jgt}:	In-hand inventory for item g in period t in DC j
DO_{jt}:	1 if DC j open in period t, 0 otherwise
M_g	Auxiliary variable representing the minimum transportation cost for product g
P_{lg}:	1 if mode l has the minimum cost for product g, 0 otherwise

Where the M_g and P_{lg} are new variables added to the existing model variables to capture and enforce the most cost-effective transportation options within the supply chain.

Objective Functions

This model incorporates two objectives, as shown below.

(a) Minimizing overall supply chain costs, including transportation, inventory, and operational costs

$$\begin{aligned}\text{Minimize } Z_1 = {} & \text{Transportation \& Shipping Costs } + \text{Inventory and Stocking Costs} \\ & + \text{Distribution Centre Setup \& Operational Costs} + \text{Supplier Disruption Costs} \\ & + \text{Minimum Transportation Cost}\end{aligned}$$

The objective function Z_1 is designed to minimize costs in various key areas of the automotive supply chain. The system combines the costs of transportation and shipping, including expenses related to all transportation activities. It also includes inventory and stocking costs, which encompass the costs of holding, additional stocking, and shortages. Additionally, it considers the setup and operational costs of distribution centers for maintaining efficient operations. The system also takes into account potential supplier failures and the associated costs. Lastly, it focuses on optimizing the least expensive routes to minimize transportation costs. This comprehensive approach attempts to improve the efficiency of the supply chain and decrease overall operational costs by improving each individual cost category.

1. Transportation and Shipping Costs:

$$\sum_{t\in T}\sum_{j\in J}\sum_{a\in A}\sum_{l\in L_m}\sum_{k\in K}((C_{lg}K_{jalkt} + (Csh1_{ja}K_{jalkt}w_{ajtg}X_{jagk}) + (Csh2_{ijtg}N_{ijtg}Y_{ijtg}))$$

This equation combines all transportation-related costs (including shipping from suppliers to DCs, from DCs to customers, and transportation costs for different modes) into one category.
This term consolidates all transportation-related costs (shipping from suppliers to DCs and DCs to customers across different modes). The innovative use of $\boldsymbol{C_{lg}}$ ensures that the most cost-effective transportation mode is selected for each product, significantly enhancing the model's ability to minimize overall supply chain costs by leveraging a multi-modal strategy.

2. Inventory and Stocking Costs**:**

$$\sum_{j\in J}\sum_{t\in T}\sum_{g\in G}\left((HV_{jgt}Ch_{jtg}) + (fE_{jt}NAS_{jtg}AS_{jt}) + (NS_{jtg}Cs_{jt}S_{jtg})\right)$$

This equation includes inventory holding costs at DCs, additional stocking costs, and costs due to shortages.

3. Distribution Centres' Setup and Operational Costs**:**

$$\sum_{t\in T}\sum_{j\in J}\left(fo_{jt}DO_{jt}\right)$$

This equation remains a separate category as it distinctly impacts the cost structure at the distribution centres.

4. Supplier Disruption Costs**:**

$$\sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{t\epsilon T}\sum_{g\epsilon G}\left(N_{ijtg}Y_{ijtg}\beta_{it}gr_{jg}\right)$$

This equation Includes the costs related to supplier disruptions.

5. Minimum Transportation Costs**:**

$$\sum_{g\in G}\left(M_g\right)$$

This remains as a separate entity as it captures the lowest possible transportation costs.

(b) Reducing the risk of disruption in the supply chain.

$$\begin{aligned} Minimize\ Z_2 = {} & Disruption\ Costs\ in\ Shipping\ from\ supplier\ to\ DC\ at\ Available\ Facilities\ (F) \\ & + Disruption\ Costs\ from\ Supplier\ to\ DC\ at\ Non-Available\ Facilities\ (NF) \\ & + \ Disruption\ Cost\ in\ Shipping\ to\ Customers\ from\ Available\ Facilities \\ & + \ Disruption\ Risks\ in\ Shipping\ to\ Customers\ from\ Non-Available\ Facilities \end{aligned}$$

Objective function Z_2 aims to minimize disruption risks within the automotive supply chain by accounting for various types of disruption-related costs. This function is segmented into four main cost components:

1. Disruption Costs in Shipping from supplier to DC at Available Facilities (F):

$$\sum_{i\epsilon I}\sum_{j\epsilon F}\sum_{t\epsilon T}\sum_{g\epsilon G}\sum_{k\epsilon K}\left(Csh2_{ijtg}\theta^k K_{jalkt}Y_{ijtg}\right)$$

This term captures the disruption risk and cost of shipping products from suppliers (i) to available distribution centers ($j\epsilon F$) for product g in period t at service level k.

2. Disruption Costs from Supplier to DC at Non-Available Facilities (NF):

$$\sum_{i\epsilon I}\sum_{j\epsilon NF}\sum_{t\epsilon T}\sum_{g\epsilon G}\sum_{k\epsilon K}\left(Csh2_{ijtg}\theta^k(1-\theta^k)K_{jalkt}Y_{ijtg}\right)$$

This term captures the compounded disruption risk of shipping from suppliers to non-available facilities ($j\epsilon NF$), where disruption risks are higher due to the unavailability of these DCs. The factor $(1-\theta^k)$ amplifies the disruption risk.

3. Disruption Cost in Shipping to Customers from Available Facilities:

$$\sum_{j\epsilon F}\sum_{a\epsilon A}\sum_{g\in G}\sum_{k\in K}\sum_{t\in T}\left(Csh1_{ja}w_{ajtg}\theta^k K_{jalkt}X_{jagk}\right)$$

This term captures the disruption risk and costs associated with shipping products from available facilities ($j\epsilon F$) to customers (a) for product g at service level k during period t. This focuses on customer-facing disruption risks.

4. Disruption Risks in Shipping to Customers from Non-Available Facilities:

$$\sum_{j\in NF}\sum_{a\in A}\sum_{g\in G}\sum_{k\in K}\sum_{t\in T}\left(Csh1_{ja}w_{ajtg}\theta^{k}(1-\theta^{k})K_{jalkt}X_{jagk}\right)$$

This term accounts for the increased disruption risk of shipping from non-available facilities $j \in NF$) to customers. The risk is compounded by the factor $(1-\theta^{k})$, reflecting the higher likelihood of disruptions due to the non-availability of the facility.

Overall, the enhance model uses a multi-modal transportation strategy to minimize supply chain disruption risks by optimizing shipments from suppliers to distribution centres (DCs) and from DCs to customers, considering both available and non-available facilities. Objective function_2 incorporate multiple transportation modes, represented by K_{jalkt}, it allows for flexible and dynamic adjustments to disruptions, enhancing overall resilience. The disruption likelihood $\theta^{k}$is used to account for varying levels of risk, ensuring robust and cost-effective decision-making throughout the supply chain.

Constraints

The model considers constraints in customer allocation, inventory management, routing, and transportation mode selection.

$$\sum_{j\in J}X_{jagk}+\sum_{j\in NF}\sum_{k\in K}\left(X_{jagk}\right)=1\ \forall a\in A, g\in G, k=0\ldots.j-1 \quad (1)$$
$$\sum_{k\in K}X_{jagk}\leq 1\ \forall a\in A, g\in G, j\in J \quad (2)$$
$$\sum_{j\epsilon J}\left(K_{jaltk}\right)-X_{jagk}\leq 1\ \forall\ l\in L_m, a\in A, t\in T, g\in G, k\in K \quad (3)$$
$$\sum_{j\in J}\sum_{g\in G}\sum_{k\in K}\left(X_{jagk}\right)=1\ \forall a\in A \quad (4)$$
$$\sum_{a\in A}\sum_{g\in G}\sum_{k\in K}\left(w_{jatg}X_{jagk}\right)\leq tx_jDO_j+ax_jAS_{jt}\ \forall j\in J, t\in T \quad (5)$$
$$\sum_{g\in G}\left(AS_{jtg}\right)+S_{jtg}\leq 1\ \forall j\in J, t\in T \quad (6)$$
$$\sum_{j\in J}\sum_{a\in A}\sum_{g\in G}\sum_{t\in T}\left(NG_{jagt}\right)=w_{ajtg}\forall a\in A \quad (7)$$
$$\sum_{j}\sum_{g}\sum_{t}\left(NAS_{jtg}\right)=ax_{jg} \quad (8)$$
$$\sum_{g\in G}\left(HV_{jgt}\right)-NS_{jgt}=\sum_{g\in G}HV_{jg(t-1)}+NAS_{jgt}+\sum_{g\in G}\sum_{i\in I}N_{ijtg}-w_{jatg}\ \forall j\in J, t\in T \quad (9)$$
$$\sum_{l\in L_m}\sum_{t\in T}\sum_{k\in K}\sum_{g\in G}\left(K_{jaltk}\right)\leq\sum_{g\in G}\sum_{k\in K}\left(X_{jagk}\right)\forall j\in J, a\in A \quad (10)$$
$$\sum_{a\in A}\sum_{l\in L_m}\sum_{k\in K}\left(K_{jaltk}\right)=1\forall a\in A, t\in T \quad (11)$$
$$\sum_{j\in J}\sum_{a\in A}\sum_{k\in K}\left(K_{jaltk}\right)\leq 1\ \forall l\in L_m, t\in T \quad (12)$$
$$\sum_{j\in J}\sum_{k\in K}\sum_{a\in A}\left(w_{jatg}K_{jaltk}\right)\leq cL_l\ \forall l\in L_m, t\in T \quad (13)$$
$$\sum_{t\in T}\sum_{k\in K}\sum_{l\in L_m}K_{jj'ltk}=0\ \forall j, j'\in J \quad (14)$$
$$M_g\leq C_{lg}+M.\left(1-P_{\boldsymbol{lg}}\right)\forall\ l\in L_m, g\in G \quad (15)$$
$$\sum_{l\in L_m}\left(P_{\boldsymbol{lg}}\right)=1\forall\ g\in G \quad (16)$$
$$\left(Y_{ijtg}, X_{jagk}, K_{jalkt}, S_{jtg}, AS_{jtg}, DO_{jt}, LC1_{ijlgtc}, LC2_{jalgtc}, LT1_{ijglt}, LT2_{jaglt}\right)\in\{0\ or\ 1\}\ \forall i,j,t,g,a,k,l,c \quad (17)$$
$$N_{ijtg}, Nd_{tg}, Qr_{tg}, NS_{jtg}, NAS_{jtg}, HV_{jgt}, sub_{cvt}\ \geq 0 \quad (18)$$

Succinctly, the constraints for the dual-objective optimization model in automotive supply chain management is defined as following:

Customer Allocation Constraints: These constraints ensure effective customer-service management. Constraint (1) guarantees each customer is assigned to a single distribution center, fulfilling all demands. Constraint (2) limits customers to one service level per DC, while Constraint (3) ensures a customer is allocated to a DC only if on the same logistical path. Constraint (4) mandates unique distributor assignments for each customer to avoid overlapping services.

Inventory Constraints: These constraints focus on inventory management efficiency. Constraint (5) stipulates that customer demand from each DC must not surpass its combined normal and safety stock capacity. Constraint (6) specifies that the choice must be made between either experiencing a stock-out or utilizing the safety stock capacity, but not both. Constraint (7) aligns customer demand from each DC with product shipments, and Constraint (8) ties the additional capacity used for a product to the DC's additional capacity. Constraint (9) computes the total product inventory per DC, accounting for authorized shortages and inventory variances.

Routing Constraints: These constraints optimize the distribution network. Constraint (10) establishes routes between customers and distributors upon allocation. Constraint (11) ensures each transportation route is assigned a single mode of transport. Constraint (12) limits distribution to one path per route, while Constraint (13) controls the transportation system's maximum carrying capacity. Constraint (14) prohibits direct routes connecting two distributors, ensuring logistical integrity

Transportation Mode Cost Constraints: Constraint (15) determines the minimum cost $\boldsymbol{M_g}$ for each product $\boldsymbol{g}$ defining it as a new constraint added to optimize cost-efficiency across the supply chain. This constraint is pivotal for ensuring that the calculated minimum cost accurately reflects the most economical transportation mode available. Constraint (16), another new addition, mandates that exactly one transportation mode is selected as the cost-minimal option. It guarantees the chosen mode for each combination of distribution center, customer, time period, and product are the most cost-effective option for transporting the product and crucial for maintaining cost-efficiency within the multi-modal transportation network.

These constraints are important to realizing the model's objectives of cost reduction and disruption risk minimization, particularly in the context of complex multi-modal transportation networks in automotive supply chains.

NSGA-II for Dual-Objective Optimization

Our research extensively employs the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for solving the multi-objective optimization problem focusing on the automotive supply chain. The NSGA-II algorithm is renowned for its effectiveness in handling complex optimization tasks, particularly those involving conflicting objectives. In our context, these objectives are twofold: minimizing supply chain costs and reducing disruption risks. Figure 3 depicts a flowchart of the NSGA-II process for implementing the proposed dual-objective optimization problem.

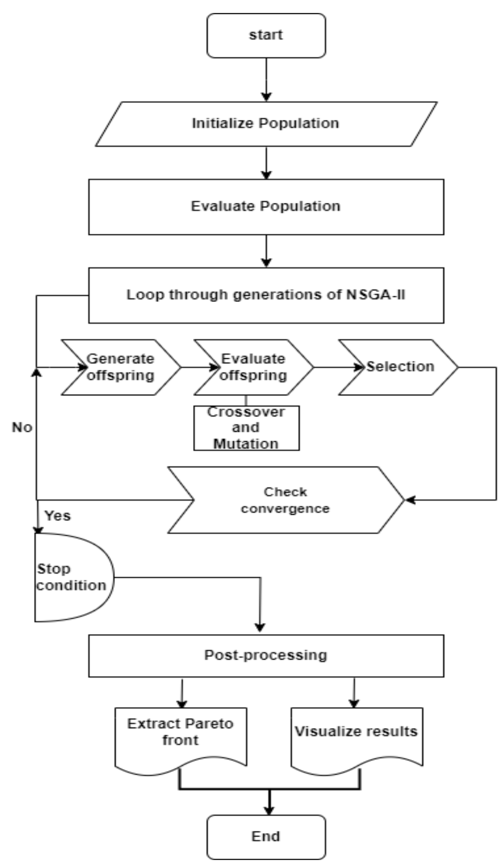

Figure 3. NSGA-II Flowchart

NSGA-II's Key Features in Our Implementation:

1. **Population-Based Approach:** Our implementation initializes a diverse population of solutions, facilitating concurrent exploration of various optimization paths. This diversity is critical for identifying efficient supply chain configurations under different scenarios, such as varying supplier reliability and transportation efficiency.
2. **Non-Dominated Sorting:** We employ non-dominated sorting to rank solutions, enabling us to focus on those that offer a balanced compromise between cost minimization and risk reduction. This method helps in categorizing solutions according to their dominance levels, ensuring a comprehensive evaluation.
3. **Crowding Distance:** To avoid convergence on a narrow part of the solution space, crowding distance is calculated, ensuring a broad and diverse set of solutions. This diversity is essential for considering all possible supply chain configurations, from transportation modes to inventory strategies.
4. **Crossover and Mutation Operators:** Through crossover and mutation, our algorithm introduces new solution traits, enhancing the search for innovative strategies that could potentially offer better performance in terms of cost and risk.
5. **Iterative Evolutionary Process:** The NSGA-II algorithm in our study evolves through generations, systematically refining solutions. Each generation is assessed, and superior solutions form the basis for the next, gradually advancing towards an optimal set.
6. **Visualization of Pareto-Front:** The Pareto-front visualization provides a clear depiction of the trade-offs between objectives, aiding decision-makers in understanding the balance between minimizing costs and reducing disruption risks.
7. **Python Implementation:** Leveraging Python and its DEAP library, our NSGA-II implementation benefits from efficient computation and flexibility, allowing for the effective handling of the complex multi-objective optimization problem of the automotive supply chain.

By integrating NSGA-II into our methodology, we aim to develop an adaptable model that effectively balances cost reduction and disruption risk minimization in automotive supply chains, ensuring resilience and efficiency in dynamic market conditions.

Computational Results and Discussion

This section explores the effectiveness of a multi-modal transportation strategy under disruption risk. We analyzed synthetic small-scale benchmark data of the automotive supply chain problem using the NSGA-II algorithm within Python to evaluate the performance of the proposed model. The study's focal point is the innovative incorporation of multi-modal transportation to achieve dual objectives: cost reduction and disruption risk minimization.

The analysis begins with the problem setup, highlighting various dimensions of small-scale problems, including the number of suppliers, distribution centers (DCs), customers, transportation modes, goods, periods, and the classification of DCs based on their failure risk. Subsequently, problem parameters generated using a uniform distribution function are detailed, laying the foundation for the linearized model's solution. Table 4 displays the dimensions of the randomly generated problems.

Table 4. Dimensions of sets in small scale

Synopsis	small-scale
Quantity of suppliers	2
Quantity of DCs	3
Quantity of customers	5
Quantity of transportation modes	4
Quantity of goods	2
Quantity of Periods	2
Total number of DCs that can fail	2
Total non-failable DC	3

The problem parameters that have been produced to be solved in the linearized model by uniform distribution function in Python are presented in Table 5

Table 5. The range of the parameters value

Parameter	small-scale
NL_{lt}:	U (1, 10)
θ^k:	U (0, 1)
β_{it}:	U (0, 1)
cL_l:	U (100, 1000)
fL_l:	U (500, 1000
Cn_{aj}	U (50, 200)
Cs_{jt}:	U (50, 100)
fo_{jt}:	U (0, 1)
$Csh1_{ja}$:	U (50, 200)
$Csh2_{ijtg}$:	U (50, 200
Ch_{jtg}:	U (50, 200)
w_{ajtg}:	U (800, 1400)
gr_{jg}	U (50, 200)
Nv_{jg}:	U (20, 50)
fE_{jt}:	U (50, 200)
OB_j:	U (1000, 100000)
ax_j:	U (500, 1000)
tx_j:	U (1500, 3000)
C_{lg}	U (50, 200)

Small Data Problems

In this study, the NSGA-II approach does not have the termination criteria. However, based on the results obtained, it is shown that this approach converges after 95 generations. The algorithm kept running until the Pareto front's fitness values changed by less than 0.01, which was set as the minimum change allowed. This happened for 10 generations in a row, making sure that the solutions were stable and the best ones for minimizing costs and disruption risk. Tables 3, 4, and 5 display the variables and the parameters value that contributed to achieving the Pareto-front of the objectives. The results section highlights the Pareto-optimal solutions obtained after 95 generations, emphasizing the critical role of binary and integer variables in deriving these solutions. Special attention is given to the decision variables M_g and $\boldsymbol{P_{lg}}$hich determine the most cost-effective transportation modes for different products. This analysis shows the model's capacity to identify optimal transportation strategies that balance cost and risk, a significant advancement over previous models that did not differentiate between transportation mode cost.

Regarding the use of minimizing the cost of transportation mode to transport automotive parts, this study's results for the auxiliary variable M_g and the binary variable ($\boldsymbol{P_{lg}}$as follows: $M_1 = 95$ when $\boldsymbol{P}_{(\boldsymbol{3},\boldsymbol{1})} = 1$ and $M_2 = 81$ when $\boldsymbol{P}_{(\boldsymbol{4},\boldsymbol{2})} = 1$. This indicates the lowest possible cost of transportation mode to transport parts of products (1 and 2) are transportation mode (3) for product 1, and transportation mode (4) for product (2).

Results Comparison

The model is further enhanced by incorporating new variables, parameters, and constraints specifically designed to optimize transportation mode costs. Notable additions include the auxiliary variable M_g which represents the minimum transportation cost for each product, and the binary variable $P_{\boldsymbol{lg}}$ which identifies if mode l offers the lowest cost for transporting product g The parameter C_{lg} has been introduced to provide a detailed cost analysis for each transportation mode used for product g. Furthermore, new constraints (17, 18) ensure that the model selects the most cost-effective transportation mode, thereby enhancing the model's efficiency in cost optimization across the supply chain.

$$Minimize\ Z_1 = \sum_{t\in T} N_{lt} \sum_{j\in J}\sum_{a\in A}\sum_{l\in L_m}\sum_{k\in K} C_{lg}K_{jalkt} + \sum_{t\in T}\sum_{j\in J} fo_{jt}DO_{jt} + \sum_{j\in J}\sum_{t\in T}\sum_{g\in G} HV_{jgt}w_{jtg}$$
$$+ \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{g\in G} Csh2_{ijtg}N_{ijtg}Y_{ijtg}(1-\beta_{it}) + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{g\in G} N_{ijtg}Y_{ijtg}\beta_{it}gr_{jg}$$
$$+ \sum_{j\in J}\sum_{g\in G}\sum_{t\in T} NS_{jtg}Cs_{jt}S_{jtg} + \sum_{j\in J}\sum_{t\in T} fE_{jt}NAS_{jtg}AS_{jt}$$
$$+ \sum_{j\in J}\sum_{a\in A}\sum_{l\in L_m}\sum_{t\in T}\sum_{l\in K}\sum_{g\in G} Csh1_{ja}K_{jalkt}w_{ajtg}X_{jagk}$$

$$Minimize\ Z_2 = \sum_{i\in I}\sum_{j\in F}\sum_{t\in T}\sum_{g\in G}\sum_{k\in K}\left(Csh2_{ijtg}\theta^k K_{jalkt}Y_{ijtg}\right)$$
$$+ \sum_{i\in I}\sum_{j\in NF}\sum_{t\in T}\sum_{g\in G}\sum_{k\in K}\left(Csh2_{ijtg}\theta^k(1-\theta^k)K_{jalkt}Y_{ijtg}\right)$$
$$+ \sum_{j\in F}\sum_{a\in A}\sum_{g\in G}\sum_{k\in K}\sum_{t\in T}\left(Csh1_{ja}w_{ajtg}\theta^k K_{jalkt}X_{jagk}\right)$$
$$+ \sum_{j\in NF}\sum_{a\in A}\sum_{g\in G}\sum_{k\in K}\sum_{t\in T}\left(Csh1_{ja}w_{ajtg}\theta^k(1-\theta^k)K_{jalkt}X_{jagk}\right)$$

In the enhanced model, the minimum cost of transportation to transport part is considered, where the objective-functions are modified based on the new developing of the problem, where the enhanced model as shown in the model above.

Regarding the modification of the model we discussed above, the results of the objective functions (minimizing overall cost (Z_1), and reducing disruption risk (Z_2)), in initial model are greater than the same objective function results (Z_1, Z_2) of enhanced model for all Pareto-front points, as shown in Table 6.

The comparative analysis shows that the enhanced model demonstrates superior performance in minimizing the objective functions. We quantitatively substantiate this improvement by comparing the objective function values between the enhanced and initial models across various Pareto-front points, conclusively demonstrating the enhanced efficiency of the proposed approach. This section discusses and displays Table 6's differences between the pareto-front results of the problem's initial model and the developed one. The initial model failed to account for the transportation mode's minimum cost, resulting in a lack of mode-based transportation cost differentiation.

Table 6. Comparison between enhanced model and existing model in pareto-front results

	enhanced model		existing model	
point	Z_1	Z_2	Z_1	Z_2
1	34445446.69	81.515	72440377.62	192.496
2	32362246.689	575.264	69969524.188	735.371
3	33346810.689	150.094	71422929.978	344.20

Based on the main purpose of the problem to minimize the objective functions, the comparison between the enhanced and initial models demonstrates that the enhanced model outperforms the initial model in all Pareto-front points for both cost reduction (Z_1) and disruption risk mitigation (Z_2). The improved model consistently demonstrates lower values in both targets, suggesting its increased efficiency and efficacy in addressing automotive supply chain difficulties. Figure 4 summarizes the results, confirming the model's significant improvement in operational efficiency and risk management.

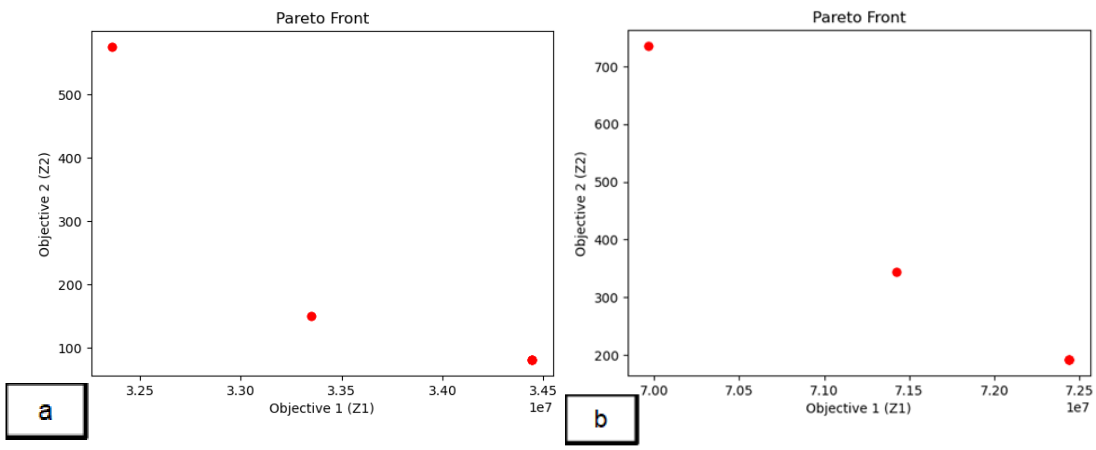

Figure 4. Comparison between enhanced Pareto-front (a) and exiting Pareto-front models (b) in NSGA-II

This demonstrates its major contribution to optimizing the supply chain. The study successfully confirmed its purpose of enhancing supply chain performance through the strategic utilization of multimodal transportation planning.

Conclusion and Recommendations

To conclude, our study delivers an enhanced mathematical model for optimizing automotive supply chains by strategically incorporating multi-modal transportation, significantly enhancing cost-efficiency and resilience against disruptions. The application of NSGA-II has been pivotal in identifying cost-effective transportation options, showcasing substantial reductions in logistics expenses and improved supply chain robustness. Our findings, backed up by detailed mathematical analysis and empirical evaluation, demonstrate the effectiveness of our enhanced model over traditional approaches. Future directions include integrating real-time data and advanced AI techniques to refine the model's precision and adaptability, promising further breakthroughs in supply chain optimization, and providing actionable insights for both academia and industry.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the content of this article. All authors have contributed to this work independently and without bias.

Acknowledgement

This research was supported by the Ministry of Higher Education under the Fundamental Research Grant Scheme (FRGS), Registration Proposal No: FRGS/1/2019/STG06/UTM/02/8, and Universiti Teknologi Malaysia (UTM) through the UTM Encouragement Research (UTMER) Grant, Cost Center No: Q.J130000.3854.31J92.

References

[1] Mohebban-Azad, E., A.-R. Abtahi, & Yousefi-Zenouz, R. (2021). A reliable location-inventory-routing three-echelon supply chain network under disruption risks. *Journal of Modelling in Management, 17*(2), 601–632.

[2] Oakey, A., Martinez-Sykora, A., & Cherrett, T. (2023). Improving the efficiency of patient diagnostic specimen collection with the aid of a multi-modal routing algorithm. *Computers & Operations Research, 157,* 106265.

[3] Pushpamali, N. N. C., ***et al.*** (2021). Stakeholder perception of reverse logistics practices on supply chain performance. *Business Strategy and the Environment, 30*(1), 60–70.

[4] Trisna, T., ***et al.*** (2016). Multi-objective optimization for supply chain management problem: A literature review. *Decision Science Letters, 5*(2), 283–316.

[5] Yoon, J., ***et al.*** (2018). Models for supplier selection and risk mitigation: A holistic approach. *International Journal of Production Research, 56*(10), 3636–3661.

[6] Dehghani Sadrabadi, M. H., ***et al.*** (2023). An integrated optimization model for planning supply chains'

resilience and business continuity under interrelated disruptions: A case study. *Kybernetes.*

[7] Saffari, H., Abbasi, M., & Gheidar-Kheljani, J. (2023). A robust, sustainable, resilient, and responsive model for forward/reverse logistics network design with a new approach based on horizontal collaboration. *Environment, Development and Sustainability.*

[8] Chen, Y., *et al.* (2023). Intelligent designs from nature: Biomimetic applications in wood technology. *Progress in Materials Science,* 101164.

[9] Cai, Z., *et al.* (2022). Design a robust logistics network with an artificial Physarum swarm algorithm. *Sustainability (Switzerland), 14*(22).

[10] Belhadi, A., *et al.* (2021). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. *Annals of Operations Research,* 1–26.

[11] Jain, M., Sharma, D. K., & Sharma, N. (2022). Artificial intelligence computing and nature-inspired optimization techniques for effective supply chain management. In *Data Analytics and Artificial Intelligence for Inventory and Supply Chain Management* (pp. 63–80). Springer.

[12] Kashem, M. A., Shamsuddoha, M., & Nasir, T. (2024). Digital-era resilience: Navigating logistics and supply chain operations after COVID-19. *Businesses, 4*(1), 1–17.

[13] Silva, P. M., *et al.* (2022). A hybrid bi-objective optimization approach for joint determination of safety stock and safety time buffers in multi-item single-stage industrial supply chains. *Computers & Industrial Engineering, 168.*

[14] Almasi, M. (2021). Sustainable supplier selection and order allocation under risk and inflation. *IEEE, 68*(3), 823–837.

[15] Feng, J., & Gong, Z. (2020). Integrated linguistic entropy weight method and multi-objective programming model for supplier selection and order allocation in a circular economy: A case study. *Journal of Cleaner Production, 277.*