Sadeghi, K., & Abadi, M. Q. H. (2023). Sustainable supply chain resilience for logistics problems: Empirical validation using robust and computational intelligence methods. Journal of Cleaner Production, 140267.

Sustainable Supply Chain Resilience for Logistics Problems: Empirical Validation Using Robust and Computational Intelligence Methods

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Abstract

A supply chain's ability to avoid an unexpected disruption or quickly return to a normal situation defines supply chain resilience. Prior works have emphasized the integration of supply chain resilience and sustainable development goals (sustainable supply chain resilience), which is the focus of this paper. This paper proposed a four-level supply chain consisting of suppliers, intermodal hubs, manufacturers, distributors along with a heterogeneous fleet of vehicles. Two types of manufacturers are included: large and small. The small manufacturers are moveable. To contribute to sustainable logistics problems, the objectives are cost, carbon emissions, and job opportunities when the appropriate supply chain members and flow of materials are optimized. To contribute to supply chain resilience, this paper presents a new robust approach and a new multiobjective algorithm to capture uncertain parameters (e.g., supply cost and employee availability). A numerical example based on empirical data shows the applicability of the proposed model.

Keywords: Supply chain resilience; Sustainable logistics; Empirical validation; Robust approach.

1. INTRODUCTION

Uncertainty is inevitable in logistics and supply chain management (Suryawanshi & Dutta, 2022). Significant input variance makes many supply chain decision-making models inefficient in times of disruption. The source of disruptions can be natural (e.g., earthquakes and wildfire) or human-made (e.g., war and cyber-attacks) (Hosseini et al., 2019). Although disruptions are infrequent, they considerably impact supply chains, particularly logistics (Suryawanshi & Dutta, 2022). Logistics, including transportation and warehousing, is what makes the flow of materials efficient, and it is the main factor in supply chain management (Sun et al., 2022). Resilience capability can contribute to logistics and supply chains by creating an ability to avoid and mitigate unprecedented disruptions. Supply chain resilience has brought considerable benefits to companies. Past empirical works indicate that resilience capability can improve the operational and financial performance of supply chains (Kamalahmadi & Parast, 2016; Kochan & Nowicki, 2018). Therefore, supply chain decision-makers place a lot of emphasis on resilience capability.

Due to possible global catastrophic risks, current trends in business include addressing sustainable development goals through multiobjective optimization approaches, particularly in logistics and supply chain management (Islam et al., 2021). Sustainable supply chain management (SSCM) refers to managing the four supply chain flows (product, information, finance, and demand) while simultaneously considering impacts on the environment, economy, and society (Seuring & Müller, 2008). A review of prior works highlighted the importance of integrating resilience and sustainability in logistics and supply chain management (Hosseini et al., 2019; Sun et al., 2022; Suryawanshi & Dutta, 2022). Integrating resilience into sustainability can result in supply chain elasticity, which refers to the ability to ensure survival and foster innovation in the aftermath of a disruption (Fang & Ge, 2023). Elasticity can assist decision-makers in managing disruptions.

Since SSCM addresses multiple objectives, multiobjective optimization has become a common technique to model a supply chain problem (Faramarzi-Oghani et al., 2022; Suryawanshi & Dutta, 2022). Prior works proposed multiobjective supply chain optimization problems to address sustainable development goals, e.g., the number of job opportunities (Pérez-Fortes et al., 2012), wealth (Boukherroub et al., 2015), regional economic value (Zahiri et al., 2017), working hours (Ramos et al., 2014), greenhouse gas (Osmani & Zhang, 2017), transportation times (Yakavenka et al., 2020), dietary health (Rohmer et al., 2019), layoffs (Vafaeenezhad et al., 2019), lead time (Wang et al., 2020), work injuries (Tautenhain et al., 2021), delivery time (Yadav et al., 2021), employment rate (Kalantari & Hosseininezhad, 2022), and disposal cost (Mogale et al., 2022). However, a few studies integrated robust and resilience concepts in multiobjective sustainable supply chain problems (Hosseini et al., 2019). For example, see Fahimnia and Jabbarzadeh (2016). Recent review papers emphasized this important gap (sustainable supply chain resilience) in prior works (Cui et al., 2022; Hosseini et al., 2019; Silva & Ruel, 2022; Suryawanshi & Dutta, 2022).

Our research question is: How can resilience and sustainability be included in decision-making models of logistics and supply chain management? In response to the research question, this paper proposes a mathematical model, explained in Section 3, in which a multiobjective approach captures the three pillars of sustainable development. Moreover, multiple concepts are used in the proposed mathematical model to address resilience, such as multiple suppliers, uncertain parameters, robust optimization, and heterogeneous manufacturers.

This paper contributes to sustainable supply chain resilience in five ways:

- First, this paper includes heterogeneous manufacturers in multiobjective supply chain problems. This paper focuses on a four-level, single-product supply chain consisting of suppliers, intermodal hubs, heterogeneous manufacturers, distributors, and a heterogeneous fleet of vehicles. Heterogeneous manufacturers can be either small or large. Small manufacturers are moveable, meaning that they can relocate periodically, while large manufacturers are fixed in their location. Heterogeneous manufacturers in the supply chain network can contribute to an agile and flexible supply chain that is resilient in times of uncertainty. Moreover, small manufacturers in crowded or geographically remote areas can participate in the supply chain.
- Second, this paper presents a new robust optimization technique to address variance in parameters due to disruptions. Robust optimization is one of the main enablers of supply chain resilience in decision-making models. Robust techniques optimize a problem by including uncertain parameters so that the solution can withstand variance. The uncertain parameters include supply-side activities and manufacturing processes.
- Third, this paper uses empirical validation for the proposed supply chain problem. In other words, the applicability of the proposed supply chain problem is shown by a numerical example based on an industrial case study. The data is collected from prior studies and governmental resources. The proposed model can be used for any single-product supply chain (e.g., cotton, recyclables, olive, avocado, and biofuel). The industrial case used in this paper is a renewable energy production called the biofuel supply chain, which is based on biomass in forests. Review of prior work emphasizes the importance of biofuel production due to its considerable role in mitigating the impacts of climate change (Suryawanshi & Dutta, 2022).
- Fourth, this paper contributes to integrating resilience and sustainability within a multiobjective optimization problem. The paper simultaneously addresses the three pillars of sustainable development and the resilience concept.

- Fifth, this paper presents a new optimization method, called the multiobjective dwarf-mongoose (MODW) algorithm, to optimize the large size of the proposed sustainable supply chain problem. An exact solver for multiple test problems validates the proposed algorithm. Moreover, the proposed algorithm is compared with three algorithms to show its performance.

The rest of the paper is organized as follows. The next section presents a review of related work. Section 3 presents the proposed supply chain problem, including its assumptions and objectives. Sections 4 and 5 show methodology and results. Section 6 presents the discussion and conclusion.

2. REVIEW OF RELATED WORK

This section reviews prior works on resilience and sustainable development in multiobjective supply chain problems. To ensure the replicability of our research, we introduce the review process of prior work as follows. ProQuest and Google Scholar platforms were used to find the prior quantitative works. In this search, we combined the keywords "resilience," "sustainable development"/ "sustainability," "multiobjective," “multiobjective,” and “supply chain” using the Boolean operator “and” between each term. ProQuest platform was selected to find papers because it has diverse scientific publishers such as Elsevier, Springer, INFORMS, Emerald, and Taylor & Francis.

2.1. Supply chain resilience

Prior review papers shows that supply chain resilience is the main capability to mitigate risk in firms (Kochan & Nowicki, 2018; Suryawanshi & Dutta, 2022). Supply chain resilience refers to an ability to avoid a disruption, minimize negative impacts of a disruption, and quickly come back to normal status during a disruption (Kochan & Nowicki, 2018; Suryawanshi & Dutta, 2022). Past works show that supply chain resilience is one of the main enablers to mitigate uncertainties and disruptions while simultaneously improving supply chain performance (Belhadi et al., 2021; Gu et al., 2021), operational performance (Laguir et al., 2022), and sustainable development performance (Cui et al., 2022). Supply chain disruptions have existed from the beginning of supply chain management, and the recent COVID-19 pandemic resulted in global awareness of the problem. Supply chain disruption can be on a global scale (e.g., international suppliers’ production halt) or a local scale (e.g., lack of labor force). Disruptions can be due to human-made disasters (e.g., war and cyber-attacks) or natural disaster (e.g., cloudy days for solar energy generation or high level of air moisture for manufacturers). Heterogeneous manufacturers significantly impact supply chain performance (Jing et al., 2022). However, due to its complexity, only a few studies have incorporated this concept into decision-making models. For instance, previous simulations research demonstrated that heterogeneous manufacturers play a vital role in mitigating fluctuations and changes (Zhu et al., 2023). Therefore, this paper contributes to supply chain resilience by considering uncertain inputs and heterogeneous manufacturers in single-product supply chains consisting of suppliers, intermodal hubs, manufacturers, and distributors. The examples for supply chains herein are cotton supply chain, glass recycle centers, olive oil supply chain, and the biofuel supply chain. Past studies developed supply chain decision models to include other risk concepts such as supply chain elasticity (Ranaiefar et al., 2013; Zhang & Xie, 2021), robustness (Baron et al., 2011; Kalantari & Hosseininezhad, 2022; Lu & Shen, 2021; Yanıkoğlu et al., 2019), stability (Ip et al., 2011; Liu et al., 2023; Ouyang, 2007), and reliability (Ebrahimi & Bagheri, 2022; Eslamipoor & Nobari, 2023; Sadeghi et al., 2014). Recent social and environmental concerns (e.g., climate change and unemployment rate) raise awareness among all supply chain communities to include sustainable development goals into their decision-making models along with risk management (Cui et al., 2022; Hosseini et al., 2019; Silva & Ruel, 2022; Suryawanshi & Dutta, 2022).

2.2. Sustainable supply chain management (SSCM)

In decision-making models, sustainable supply chain management includes the three pillars of sustainable development (the economy, the environment, and the society) (Seuring & Müller, 2008). Thus, SSCM includes green logistics and supply chain management and considers social and economic indices in the decision-making models.

To consider environment impacts on supply chains, prior works have included environmental indices such as carbon emissions (Kalantari & Hosseininezhad, 2022) and air pollution (Peng et al., 2018). Carbon emission is the main environmental indicator to be included in the supply chain decision-making models. Carbon emissions can be generated in supply chains due to employee commuting (Boukherroub et al., 2015), manufacturing processes (Kalantari & Hosseininezhad, 2022), and transportation activities (Rezaei & Kheirkhah, 2018), all of which are included in the proposed model.

There are various social indices captured by supply chain models such as wealth (Boukherroub et al., 2015), working hours (Ramos et al., 2014), dietary health (Rohmer et al., 2019), layoffs (Vafaeenezhad et al., 2019), work injuries (Tautenhain et al., 2021), and employment rates (Kalantari & Hosseininezhad, 2022). To include social concerns in the decision-making model, this paper captures local employment (Boukherroub et al., 2015) and the number of jobs created (Kalantari & Hosseininezhad, 2022; Pérez-Fortes et al., 2012; Rezaei & Kheirkhah, 2018) in the proposed supply chain model.

The main economic indices are costs, which can include a variety of operations and supply chain activities such as transportation, facility and production, and supply and inventory.

Since the three pillars of sustainable development have three different units, the multiobjective optimization modeling approach is inevitable. The multiobjective optimization simultaneously solves conflicting objectives while providing optimal or near-optimal solutions for the problem. Another approach to solving a multiobjective SSCM problem is converting all objectives into one unit. Some prior works converted environmental and social indices into economic considerations such as disposal cost (Mogale et al., 2022). The conversion of social and environmental indices into cost index can create a solution biased on sustainable development's economic pillar. For example, it is not ethical to convert workers' fatal injuries into cost index in the decision-making models because then the models will prefer a beneficial economic investment over a worker's life. Thus, we include the three pillars of sustainable development in three different objectives through a multiobjective optimization problem.

2.3. Multiobjective optimization

The use of multiobjective optimization problems is increasing in supply chain management. Multiobjective techniques provide a set of optimal or near-optimal solutions for decision-makers. A Pareto optimal solution is a set of solutions in which there is no room for improving any objectives without impairing at least one of the other objectives. In other words, none of the solutions can be dominated by any other solutions. This multiobjective optimization can simultaneously consider conflicting objectives and provide various optimal solutions for decision-makers. However, a recent review paper showed that multiobjective optimization has been used in only 25% of prior works in supply chain management studies (Suryawanshi & Dutta, 2022). Meta-heuristic algorithms are viable for multiobjective optimization problems (Komaki et al., 2017; Sheikh et al., 2019; Tavana et al., 2018). Faramarzi-Oghani et al. (2022) reviewed prior work employing meta-heuristic algorithms to optimize sustainable supply chain problems. Meta-heuristic algorithms are one of the main approaches to computational intelligence (Chowdhury et al., 2021; Jabbari et al., 2022; Jafarian et al., 2020; Shahvari et al., 2022). Prior works employed a variety of meta-heuristic algorithms to provide Pareto solutions (Gunantara, 2018), such as a cross-entropy-based optimization algorithm (Kalantari & Hosseininezhad, 2022). However, this paper proposes a new revised version of a meta-heuristic algorithm: multiobjective dwarf-mongoose (MODW) algorithm. This paper contributes to multiobjective optimization by proposing a new algorithm.

2.4. Robust optimization

Robustness is one of the main enablers of resilience management. Robustness protects and maintains the supply chain operations by addressing unexpected variance of inputs in decision-making models during disruptions. Robust optimization refers to solving a problem while addressing uncertain inputs (Baron et al., 2011; Kalantari & Hosseininezhad, 2022; Lu & Shen, 2021; Yanıkoğlu et al., 2019). In mathematical models, decision-makers have recently placed much importance on the application of robust optimization since it can contribute to creating resilience against random inputs such as demand (Lu & Shen, 2021; Yanıkoğlu et al., 2019). Lu and Shen (2021) and Yanikoglu et al. (2019) provided a review of robust optimization used in past studies. Robust optimization is used in various areas such as facility location (Baron et al., 2011), food supply chain (Kalantari & Hosseininezhad, 2022), and healthcare supply chain (Shang et al., 2022). This paper contributes to robust optimization works by proposing a new method, called the pessimistic fuzzy robust (PFR), based on the method presented by Babazadeh et al. (2017).

2.5. Supply chain case: Biofuel supply chain

The application of an industrial case in a mathematical model can provide an empirical validation to show the applicability of the model. To produce and deliver a single product, the proposed supply chain model consists of four levels: raw material suppliers, supply hubs (or intermodal hubs), manufacturers, and distribution centers (warehouses). For the empirical validation, there are many cases to be used in the proposed supply chain such as cotton supply chain, glass recycling centers, olive oil supply chain, and biofuel supply chain. This paper selects the biofuel energy supply chain as a case to show the applicability of the proposed supply chain model since it has considerable impacts on sustainable development (see Section 4.1). A common biofuel supply chain consists of four levels: suppliers, intermodal hubs (or collection facilities), manufacturers (biorefineries), and distribution centers (Marufuzzaman & Ekşioğlu, 2017; Memişoğlu & Üster, 2016). Recent review papers provided a comprehensive list of prior works in biofuel supply chains for interested readers (e.g., Guedes et al., 2018; Ko et al., 2018; Kumar & Strezov, 2021; Pinheiro Pires et al., 2019). Prior works included sustainable development into biofuel supply chains, e.g., storage conditions (Pérez-Fortes et al., 2012), social concerns (Cambero & Sowlati, 2016), and stochastic parameters (Osmani & Zhang, 2017). However, there is little information about heterogeneous manufacturers and large-scale optimization problems. Likewise, little is known about robust optimization and uncertainty in biofuel supply chains. These issues are considered in this paper.

3. THE PROPOSED MODEL: SUSTAINABLE SUPPLY CHAIN RESILIENCE

This paper focuses on a four-level supply chain delivering a single product made from a single raw material. Examples include cotton supply chain, glass recycling centers, olive oil supply chain, and biofuel supply chain. The first level consists of raw material suppliers ($i \in I$). These suppliers can send raw materials (X) to either the second or third level. The second level consists of storage depots ($k \in K$), which are intermodal hubs where supplied raw materials are loaded on a bigger truck. The third level consists of heterogeneous manufacturers. There are two types of manufacturers: small and large. Small manufacturers ($j \in J$) can be temporarily established in a location and move to another location between production periods. Practical examples are mobile emergency rooms, food trucks, and mobile biorefinery. Large manufacturers ($l \in L$) are fixed and have a higher level of production than small manufacturers. The manufacturers will send the final product (Y) to the fourth level of the supply chain, which is the distribution center ($w \in W$) (sometimes called distributors or warehouses).

All levels are affected by employee commutes; however, for the purposes of this study, only employees who commute from residential areas ($a \in A$) to manufacturers are included in calculations. This parameter was set because there is significant variation in the number of employees working at different manufacturers. The model uses a heterogeneous fleet of vehicles ($r \in R$) for transportation of materials and workers between supply chain members. Moreover, the distance between any two supply chain members is known. Figure 1 represents the proposed supply chain network.

Each residential area of a has a certain number of employees available to work, symbolized by n_a, while employees work b hours per day. The price of raw materials is p per unit. All raw material suppliers have a total supply capacity of F. Manufacturers have a material utilization of S. Each manufacturer has production capacity g_λ, a fixed number of employees e_λ, and a set number of labor hours for producing one unit of product H_λ, in which $\lambda \in \{J, L\}$. Intermodal hubs, manufacturers, and distributors have a storage capacity of B_θ, opening or selecting cost c_θ, and operating cost o_θ, in which $\theta \in \{J, K, L, W\}$. There are transportation costs ($C^r_{\omega\omega'}$) and transportation capacity ($Q^r_{\omega\omega'}$) for the product flow between supply chain members using vehicle type r, in which $\omega \neq \omega' \in \{I, J, K, L, W\}$.

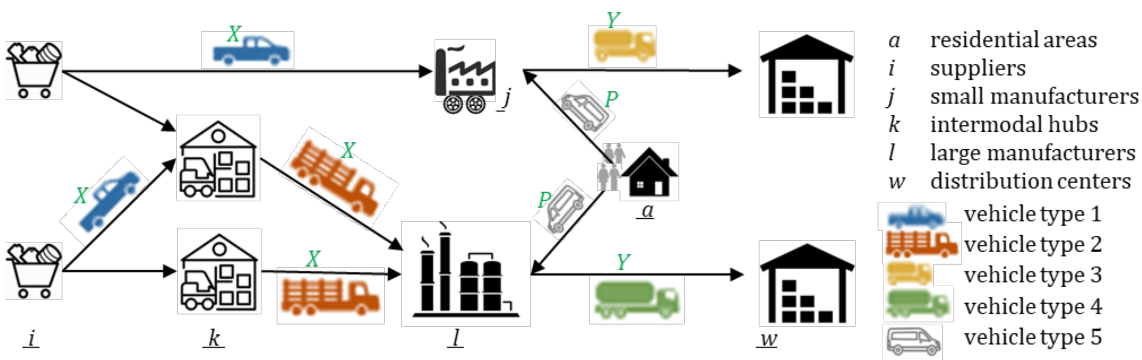

Figure 1: A four-level supply chain network of a single-product

3.1. Supply chain objectives

When supply chain objectives are optimized, the optimal solution consists of three parts: number of individuals who live in urban areas and work at manufacturing plants; flow of raw material and final product in the supply chain network; and supply chain member selection. To address SSCM, we consider three objectives in the proposed supply chain: the economic, environmental, and societal objectives. Resilience and sustainable logistics are interwoven in the proposed supply chain. Sustainability goals are addressed through objective functions. The resilience of parameters and variables is tackled using a novel robust optimization approach known as the possibilistic mean-absolute deviation method (discussed in Section 5.2).

3.1.1. Economic performance

In this paper, the economic function consists of facility location costs including opening and selecting, transportation costs, and raw material costs. Decision-makers can calculate the final price of the product by dividing the economic function by the amount of final product.

3.1.2. Environmental performance

To include environmental impacts of the proposed supply chain, this paper captures carbon dioxide equivalent (CO2e) for manufacturing processes (Kalantari & Hosseininezhad, 2022), transportation of materials and products (Rezaei & Kheirkhah, 2018), and employees' commuting miles (Boukherroub et al., 2015).

3.1.3. Societal performance

This paper uses two social indices, job opportunities (Pérez-Fortes et al., 2012; Rezaei & Kheirkhah, 2018) and local employment (Boukherroub et al., 2015). The local employment goal can be addressed when the model minimizes commuting distance (Boukherroub et al., 2015) by minimizing the carbon footprint of commuting. This model already minimized carbon footprint, so the factor of local employment is excluded to avoid redundancy (Boukherroub et al., 2015). This paper focuses on number of jobs created in manufacturing sites.

3.2. Supply chain constraints

- This paper uses the Big M method to formulate the status of supply chain members by which $z_\theta = \{0\text{: close or not selected; } 1\text{: open or selected}\}$, where $\theta \in \{J, K, L, W\}$. For example, $\sum_i X_{ik} \leq B_k z_k$ indicates that raw materials from supplier i will be sent only to the small manufacturer k that is open (working). In other words, this equation identifies the link between suppliers and manufacturers.
- There is a total supply capacity of F. In other words, F represents the total amount of raw material available from all suppliers combined.
- There is a balance between the input and output of supply chain members, e.g., $\sum_i X_{ik} = \sum_l X_{kl}, \forall k \in K$.
- Manufacturers have a material utilization of S, e.g., ($S_j \times \sum_i X_{ij} = \sum_w Y_{jw}, \forall j \in J$). Each manufacturer has a production capacity of g_λ, where $\lambda \in \{J, L\}$, e.g., $Y_j \leq g_j, \forall j \in J$.
- There is a constraint on the number of employees available to work. To calculate the number of individuals working in manufacturing sites, we need to obtain number of worker-hours to generate one unit of service or goods and then divide it by the worker's working capacity, e.g., $\sum_a P_{aj} = e_j \times z_j + \lceil (H_j \times \sum_w Y_{jw})/b \rceil, \forall j \in J$.

3.3. Mathematical model

The mathematical notations used in this paper are as follows.

Indices

a	Residential area index, $a \in A$
i	Raw materials suppliers index, $i \in I$
j	Small manufacturers index, $j \in J$
k	Intermodal hub index, $k \in K$
l	Large manufacturers index, $l \in L$
r	Vehicle types index, $r \in R$
w	Warehouse sites or distribution centers index, $w \in W$

Capacity Parameters

b	Individuals' daily working hours
F	Total supply capacity of raw material suppliers
n_a	Employees available in the residential area a

Location Parameters

B_θ	Storage capacity, $\theta \in \{J, K, L, W\}$
c_θ	Opening or selecting cost, $\theta \in \{J, K, L, W\}$
o_θ	Operating cost, $\theta \in \{J, K, L, W\}$

Manufacturers' Parameters

e_λ	Number of manufacturers' permanent workers, $\lambda \in \{J, L\}$
g_λ	Production capacity of manufacturers, $\lambda \in \{J, L\}$
H_λ	Number of work hours required by each manufacturer to produce one unit of product, $\lambda \in \{J, L\}$
p	Raw material price
S_λ	Manufacturers' material utilization, $\lambda \in \{J, L\}$

Transportation Parameters

$C^r_{\omega\omega'}$ Transportation cost between supply chain members using vehicle type r, $\omega \neq \omega' \in \{I, J, K, L, W\}$

$D_{ss'}$ Distance between locations, $s \neq s' \in \{A, I, J, K, L, W\}$

M Big M (large positive constant)

$Q^r_{\omega\omega'}$ Capacity of vehicle type r for transportation from location ω *to* ω', $\omega \neq \omega' \in \{I, J, K, L, W\}$

CO2e Coefficient Parameters

α Kg CO2e per worker-mile traveled

β Kg CO2e per one unit of production

γ_r Kg CO2e per mile for vehicle type r

Decision Variables

$P_{a\lambda}$ Number of individuals or employees who live in area a and work in manufacturing sites, $\lambda \in \{J, L\}$

X_{ij} Quantity of raw materials transferred from i to j

X_{ik} Quantity of raw materials transferred from i to k

X_{kl} Quantity of raw materials transferred from k to l

Y_{jw} Quantity of final products transferred from j to w

Y_{lw} Quantity of final products transferred from l to w

z_θ Status of supply chain members {0: close or not selected; 1: open or selected}, where $\theta \in \{J, K, L, W\}$

Min Z_1:

$$\left\{p\left(\sum_i \sum_j X_{ij} + \sum_i \sum_k X_{ik}\right)\right\} + \left\{\sum_i \sum_j \sum_r C^r_{ij} D_{ij} \lceil X_{ij}/Q^r_{ij} \rceil + \sum_i \sum_k \sum_r C^r_{ik} D_{ik} \lceil X_{ik}/Q^r_{ik} \rceil + \sum_k \sum_l \sum_r C^r_{kl} D_{kl} \lceil X_{kl}/Q^r_{kl} \rceil + \sum_j \sum_w \sum_r C^r_{jw} D_{jw} \lceil Y_{jw}/Q^r_{jw} \rceil + \sum_l \sum_w \sum_r C^r_{lw} D_{lw} \lceil Y_{lw}/Q^r_{lw} \rceil\right\} + \left\{\left(\sum_k c_k z_k + \sum_l c_l z_l + \sum_j c_j z_j + \sum_w c_w z_w\right) + \left(\sum_k \left(\sum_l X_{kl}\right) o_k + \sum_j \left(\sum_w Y_{jw}\right) o_j + \sum_l \left(\sum_w Y_{lw}\right) o_l + \sum_w \left(\sum_j Y_{jw} + \sum_l Y_{lw}\right) o_w\right)\right\} \quad (1)$$

Min Z_2:

$$\{\alpha(\sum_a \sum_j D_{aj} P_{aj} + \sum_a \sum_l D_{al} P_{al})\} + \{\beta(\sum_l \sum_w Y_{lw} + \sum_j \sum_w Y_{jw})\} +$$
$$\{\sum_r \sum_i \sum_j D_{ij} \lceil X_{ij}/Q_{ij}^r \rceil \gamma_r + \sum_r \sum_i \sum_k D_{ik} \lceil X_{ik}/Q_{ik}^r \rceil \gamma_r + \sum_r \sum_k \sum_l D_{kl} \lceil X_{kl}/Q_{kl}^r \rceil \gamma_r +$$
$$\sum_r \sum_j \sum_w D_{jw} \lceil Y_{jw}/Q_{jw}^r \rceil \gamma_r + \sum_r \sum_l \sum_w D_{lw} \lceil Y_{lw}/Q_{lw}^r \rceil \gamma_r\} \tag{2}$$

Max Z_3:

$$\{\sum_j \lceil (H_j \times \sum_w Y_{jw})/b \rceil + \sum_l \lceil (H_l \times \sum_w Y_{lw})/b \rceil\} + \{\sum_j e_j z_j + \sum_l e_l z_l\} \tag{3}$$

Subject to:

$$\sum_j X_{ij} + \sum_k X_{ik} \geq F_i \quad \forall i \in I, \tag{4}$$
$$\sum_i X_{ik} \leq B_k z_k \quad \forall k \in K, \tag{5}$$
$$\sum_i X_{ij} \leq B_j z_j \quad \forall j \in J, \tag{6}$$
$$\sum_k X_{kl} \leq B_l z_l \quad \forall l \in L, \tag{7}$$
$$\sum_j Y_{jw} + \sum_l Y_{lw} \leq B_w z_w \quad \forall w \in W, \tag{8}$$
$$\sum_i X_{ik} = \sum_l X_{kl} \quad \forall k \in K, \tag{9}$$
$$\sum_j Y_{jw} + \sum_l Y_{lw} = Y_w \quad \forall w \in W, \tag{10}$$
$$S_j \times \sum_i X_{ij} = \sum_w Y_{jw} \quad \forall j \in J, \tag{11}$$
$$S_l \times \sum_k X_{kl} = \sum_w Y_{lw} \quad \forall l \in L, \tag{12}$$
$$Y_j \leq g_j \quad \forall j \in J, \tag{13}$$
$$Y_l \leq g_l \quad \forall l \in L, \tag{14}$$
$$\sum_a P_{aj} = e_j \times z_j + \lceil (H_j \times \sum_w Y_{jw})/b \rceil \quad \forall j \in J, \tag{15}$$
$$\sum_a P_{al} = e_l \times z_l + \lceil (H_l \times \sum_w Y_{lw})/b \rceil \quad \forall l \in L, \tag{16}$$
$$\sum_j P_{aj} + \sum_l P_{al} \leq n_a \quad \forall a \in A, \tag{17}$$
$$X_{ij}, X_{ik}, X_{kl}, Y_{jw}, Y_{lw} \geq 0 \quad \forall i \in I, \forall j \in J, \forall k \in K, \forall l \in L, \forall w \in W \tag{18}$$
$$z_j, z_k, z_l, z_w = \{0,1\} \quad \forall j \in J, \forall k \in K, \forall l \in L, \forall w \in W \tag{19}$$
$$P_{aj}, P_{al} \geq 0, int \quad \forall a \in A, \forall i \in I, \forall j \in J \tag{20}$$

Objective functions are given in Eqs. (1-3) as follows. Eq. (1) captures the economic objective to minimize the costs. The first curly brackets ("{}") show the raw material cost. The second curly brackets include transportation cost (*cost × distance × number of vehicle trips*). The third curly brackets include facility costs of each level (*fixed and variable costs*).

Note that $\lceil X_{ij}/Q_{ij}^{r} \rceil$ is the number of vehicle trips from i to j. In this paper, we convert ceil terms (e.g., $\lceil X_{ij}/Q_{ij}^{r} \rceil$) using the Ceiling Function Transformations Method explained by Asghari et al. (2022).

Eq. (2) captures the environmental objective to minimize carbon dioxide equivalent (CO2e). The first curly brackets show CO2e of employees commuting (α, kg CO2e per worker-mile traveled) (Boukherroub et al., 2015). The second curly brackets include CO2e of manufacturing (β, kg CO2e per one unit of production). Manufacturers' carbon footprint is the product of amount of production and the manufacturing carbon emission factor. The third curly brackets calculate CO2e of transportation (γ_r, kg CO2e per mile) (Rezaei & Kheirkhah, 2018). Note that CO2e includes greenhouse gases such as carbon dioxide, methane, and nitrous oxide.

Eq. (3) addresses the social impacts of the proposed model by maximizing the number of job opportunities (Pérez-Fortes et al., 2012; Rezaei & Kheirkhah, 2018). The first curly brackets calculate the number of employees based on production activities in manufacturing sites. The second curly brackets measure the fixed number of employees in manufacturing sites.

The objective functions are limited to constraints shown in Eqs. (4-20) as follows. Eq. (4) shows that all raw material suppliers have a total supply capacity of F. Eqs. (5-8) indicate the chosen route for transportation flow and the transportation capacity along the route (who sends how much to whom). Eqs. (9-10) create a balance between the input and output of transportation flow between supply chain members. Eqs. (11-12) show that manufacturers have a material utilization of S. Eqs. (13-14) check manufacturers' production capacity. Eqs. (15-16) calculate the number of manufacturers' employees. Note that there are b hours per day for each worker. Eq. (17) shows that each residential area has a certain number of employees available to work. Eqs. (18-20) define the decision variables. Note that non-linear relationships such as Eqs. (15-16) are linearized using the techniques proposed by Asghari et al. (2022).

4. METHODOLOGY

This paper employs the multiobjective optimization approach to optimize objective functions by finding the optimal value of each decision variable. Scalarization and Pareto methods are common approaches to solving multiobjective problems (Faramarzi-Oghani et al., 2022; Gunantara, 2018). The scalarization methods transfer multiple objectives into one objective, while the Pareto methods find a set of optimal or near-optimal solutions. This paper employs both methods. First, this paper uses a scalarization method, the weighted goal programming technique (Boukherroub et al., 2015), to evaluate the proposed model. Second, this paper uses a new Pareto method, multiobjective dwarf-mongoose (MODW) algorithm, to evaluate the proposed large-size model, including uncertain inputs.

The general algebraic modeling system (GAMS) language, Cplex solver, is used to provide the optimal solutions for the proposed small-size supply chain model. Moreover, this paper develops a new algorithm to optimize the proposed large-size model. We used MATLAB language programming to perform the proposed algorithm. The code is available on www.GitHub.com/naricode/Data2023JCP.

To address uncertainty in the inputs of the proposed model, this paper uses robust optimization. To validate the performance of the proposed method, we compare its results with the standard version of the method. Moreover, to provide the empirical validation and the applicability of the proposed model, this paper uses a supply chain case.

4.1. Supply chain case: Application of the proposed supply chain model

To show the applicability of the proposed supply chain model, we select a renewable supply chain problem in which biofuel is produced from forest biomass. The use of an empirical case can increase the validation of the proposed mathematical model. According to Figure 1, raw materials suppliers are harvesting sites while intermodal hubs are collection sites. Small manufacturers are small refineries, which can change their locations between periods. Large manufacturers are large biofuel refineries. The rest of the parameters and variables explained in the mathematical notations are applied to this case.

There are two main reasons why this case is selected for the proposed model. First, renewable energies based on forest biomass have a considerable impact to reduce wildfire risk. A 2021 report showed that 10.1 million acres were burned in the US due to 58,950 wildfires (Congressional Research Service, 2022). Dried biomass in forests is the main enabler of wildfires (Madrigal et al., 2017). Combustible forest biomass is a free raw material for producing energy sources, such as biofuel (Madrigal et al., 2017). Second, the academic community has recently demanded more research on renewable supply chains such as biofuel (Suryawanshi & Dutta, 2022). In this paper, Oregon forests are selected for the case study because it is one of the states experiencing severe wildfires. Moreover, Oregon has an unemployment rate higher than the national average and a low gross domestic product.

4.2. Variables

The three main decision variables used in the proposed supply chain model are the number of employees, flow of raw material and final product in the supply chain network, and supply chain member selection. The outcomes are the total costs, the total CO2e, and the number of job opportunities. Parameters are explained in Section 3.3, mathematical notation.

4.3. Data

The data is collected from prior studies and governmental resources.

We chose four counties in Oregon based on their forests' density of biomass. In other words, we selected areas with a significant number of bone-dry tons (BDT) of net biomass available (F). The selected counties are Washington (6.1 BDT millions), Tillamook (13.2 BDT millions), Columbia (6.1 BDT millions), and Clatsop (11.5 BDT millions) (OSU, 2017). Suppliers provide the raw material, biomass, for $p = \$25$ per ton (U.S. EPA, 2017) to produce the final product of biofuel, which is \$3.64 per gallon in the 2022 market (Dzhuraeva, 2022).

To identify potential supply chain members, we explored two databases that are accessible in ArcGIS software (version 10.5.1). The databases used are "State of Oregon Geospatial Enterprise Office" and "the US Forest Service, Oregon Department of Transportation." We identified potential supply chain members including $W = 4$ distribution centers (warehouses), $J = 7$ small manufacturers, $L = 4$ large manufacturers, $K = 9$ intermodal hubs, $I = 43$ suppliers, and $A = 4$ employee residential areas (Portland, Tillamook, St. Helens, and Astoria). To calculate the distance between supply chain members including residential areas, $D_{ss'}$ where $s \neq s' \in \{A, I, J, K, L, W\}$, the shortest paths were determined using Google's application programming interface (API) with R programming language. Appendix includes the geographical information of potential supply chain members.

The quantity of available workers or employees (n_a) is obtained by product of the unemployment rate by the population in each city. The value for n_a in each city is as follows: Astoria = 407, St. Helens = 553, Tillamook = 212, and Portland = 25102. Potential employees have the required skills for working in manufacturing sites. In each manufacturing site, there are 9 employees (e_λ) who have 0.218 person-hours per ton-year to produce 1 ton of biofuel (Mullaney et al., 2002).

Manufacturers' material utilization, S_λ, is 0.5. Small manufacturers have the same storage capacity (B_θ) and production capacity (g_λ) of 1,650 thousand liters (or 1,650×0.264 thousand gallons) per year. Large manufacturers have 43,930 thousand liters per year. The storage capacity of suppliers and intermodal hubs are 1,025 and 1,650 tons, respectively. Opening or selecting costs, c_θ, of small and large manufacturers are \$158,489 and \$769,834, respectively. Opening costs or ~~selecting~~selection costs for suppliers and warehouses are assumed to be zero. Operating costs, o_θ, of small and large manufacturers are \$41.32 and \$41.15 per ton, respectively. Operating costs for suppliers and warehouses are assumed to be \$2 per ton (OSU, 2017).

There are four types (r = 4) of vehicles in the proposed supply chain network, shown in Figure 1. The overall cost of vehicle transportation is \$4.98 per ton/hour, $C^r_{\omega\omega'}$. Each vehicle has a capacity of *small tractor-trailer*=14.99, *large tractor-trailer*=29.98, *small tanker trailer* =20.06, and *large tanker trailer*=40.12, $Q^{r=1:4}_{\omega\omega'}$.

Prior studies indicated that the average net life-cycle CO2e of biomass pyrolysis is 0.024 kg per MJ (=[60.58 − 12.49]/2) (Yang et al., 2021). This paper uses an estimate proposed by Steele et al. (2012) in which CO2e of biofuel, β, is around 0.0323 kg per MJ of biofuel. It is assumed that 1 kilogram of biofuel contains 18 MJ energy and 1.20 kg per liter density at 158C (Steele et al., 2012). Note that β is adjusted to include higher heating value energy (×18) and to account for the density of biofuel (×1.2) (Steele et al., 2012). A 12-passenger van is used for employees commuting, which is assumed to have a CO2e of 45×0.485/12 kg per passenger-mile (U.S. EPA, 2015). Thus, α is 0.04 = 0.485/12. The CO2e of other types of vehicles (γ_{r}) are small-tractor=0.029, large-tractor=0.051, small-tanker=0.21, and large-tank=0.043 kg per ton-mile. It is assumed that on average vehicles carry about 43 tons, thus, γ_{r} would be adjusted for each trip by ×43.

4.4. Proposed methods

This paper proposed an improved version of a robust optimization method and developed a new multiobjective algorithm, which is explained in the next section along with the validity.

5. RESULTS AND PROPOSED METHODS

Three subsections provide results of the proposed model. First, this paper focuses on the empirical validation of the proposed model based on hand-collected biofuel supply chain data. The second subsection improves a robust optimization method to address important uncertain parameters. The third subsection presents a new multiobjective algorithm to optimize large-size problems.

5.1. Results of the biofuel supply chain case: Scalarization method

Table 1 shows the results of the proposed model based on hand-collected data. We use the weighted goal programming technique to optimize the model (Boukherroub et al., 2015). Table 2 compares the proposed model to a model with homogeneous manufacturers (traditional model). The results show that the proposed model has a better performance regarding objectives and biofuel price. The proposed model decreases biofuel cost from \$3.32 to \$1.05 per gallon. Heterogenous manufacturers (e.g., movable manufacturers) can better address low levels of demand. Moreover, movable manufacturers can access areas that are difficult to reach by fixed manufacturers. The proposed model has a considerable impact on carbon saving ~~because as~~because the minimum amount of CO2e is 3,508 kg when the focus in on CO2e optimization.

Note that we performed the sensitivity analysis by considering low- and high-level values for cost drivers such as facility, operating, warehouse, and raw material costs. The results show that they positively correlate with the economic objective, as expected. Moreover, manufacturing utilization oscillations considerably impact the economic and environmental objectives.

Table 1: Results of biofuel supply chain case

	Weighting objectives

Objective	$(Z_1,0,0)$	$(0,Z_2,0)$	$(0,0,Z_3)$
Cost ($)	819,756	5,586,827	7,588,582
CO2e (kg)	5,393	3,508	55,677
Job (position)	100	132	352
Biofuel price ($/gal)	1.34	9.16	3.22

Table 2: Comparison between proposed model and traditional model

Variables	Proposed model	Traditional model
Cost of biofuel	$1.05/gal	$3.32/gal
CO2e of commuting	117 kg CO_2e	99 kg CO_2e
CO2e of conversion processes	1609 kg CO_2e	1609 kg CO_2e
CO2e of transportation	2515 kg CO_2e	1955 kg CO_2e
Total CO2e	4241	3663
The number of jobs created	100 people	100 people

5.2. Proposed robust technique: Pessimistic fuzzy robust (PFR) method

This paper improves a robust optimization method, called the possibilistic mean-absolute deviation method, presented by Babazadeh et al. (2017). Babazadeh et al.'s method (2017) uses fuzzy theory to capture uncertain input. Compared with Babazadeh et al.'s method (2017), we used the standard deviation of errors rather than the absolute value of deviations.

The proposed robust method considers three possible events based on the severity of disruption: optimistic, realistic, and pessimistic events. A triangular fuzzy number (e.g., $\tilde{A}$), shown with "~," is selected because it has three members ($\tilde{A} = \{A^I, A^{II}, A^{III}\}$) with different possibilities to consider. Interested readers can see Klir and Yuan (1996) to review the fuzzy calculations. These three members can be linked with the three possible events explained above.

To address an uncertain parameter (e.g., A) influencing a decision variable (e.g., x) in objective functions (e.g., $f(x)$), the proposed robust method includes the minimal mean of a fuzzy outcome (e.g., $\mu(\tilde{A}x)$) and its standard deviation ($\sigma(\tilde{A}x)$) adjusted by the pessimistic situation (e.g., by ω). Moreover, when a constraint includes an uncertain parameter, the pessimistic approach focuses on those sides that fall in the infeasible solution area or restrict the feasible solution area. But the optimistic approach focuses on those sides that fall in the feasible solution area or do not restrict the feasible solution area.

We weight (e.g., by θ) the fuzzy members to address the worst possible value for uncertain parameters. We call this method the pessimistic fuzzy robust (PFR) method.

$$\text{If } f(Ax) \rightarrow f(\mu(\tilde{A}x) + \omega(\sigma(\tilde{A}x))) \quad (21)$$

$$\text{If } Ax \geq B \rightarrow \lfloor \tilde{A}x \rceil \geq \lceil \tilde{B} \rceil \quad (22)$$

$$\text{If } Ax \leq B \rightarrow \lceil \tilde{A}x \rceil \leq \lfloor \tilde{B} \rceil \quad (23)$$

$$\text{If } Ax = B \rightarrow \left(\lceil \tilde{B} \rceil \leq \lfloor \tilde{A}x \rceil\right) \cup \left(\lceil \tilde{A}x \rceil \leq \lfloor \tilde{B} \rceil\right) \quad (24)$$

In Eq. (21), x is a decision variable, and $\tilde{A}$ and $\tilde{B}$ are the triangular fuzzy version of A and B. The pessimistic approach in the objective function, $f(x)$, is captured by ω to emphasize the output variation.

In Eq. (21), μ and σ are the mean and standard deviation, respectively, in which $\mu(\tilde{A}x) = (A^{I} + 4A^{II} + A^{III})/6$ and $\sigma(\tilde{A}x) = \sqrt{((A^{III} - A^{1})^{\mathrm{II}})/24}$ (Almaraz Luengo, 2010).

$\lfloor\ \rceil$ and $\lceil\ \rceil$ refer to weighing fuzzy numbers' left and right tails, respectively. For example, In Eq. (22), $\lceil \tilde{B} \rceil$ refers to weighing the second and the third element of $\tilde{B}$ (B^{II} and B^{III}) using 0<θ<0.5. This $\lceil \tilde{B} \rceil$ represents a bigger value of B that restricts the feasible solution area using the pessimistic approach. From feasible area perspective, $\lfloor \tilde{A}x \rceil$ refers to weighing the first and the second element of $\tilde{A}$, which represents a smaller area of A that restricts the feasible solution area. It is assumed that a triangular fuzzy number's right and left sides can be defined as $(A^{I} + 2A^{II})/3$ and $(2A^{II} + A^{III})/3$, respectively (Babazadeh et al., 2017). Thus, Eq. (22) can be simplified as,

$$x\left((1-\theta)\left(\frac{A^{I}+2A^{II}}{3}\right) + \theta\left(\frac{2A^{II}+A^{III}}{3}\right)\right) \geq \left(\theta\left(\frac{B^{I}+2B^{II}}{3}\right) + (1-\theta)\left(\frac{2B^{II}+B^{III}}{3}\right)\right) \quad (22.a)$$

Similarly, Eq. (23) is,

$$x\left(\theta\left(\frac{A^{I}+2A^{II}}{3}\right) + (1-\theta)\left(\frac{2A^{II}+A^{III}}{3}\right)\right) \leq \left((1-\theta)\left(\frac{B^{I}+2B^{II}}{3}\right) + \theta\left(\frac{2B^{II}+B^{III}}{3}\right)\right) \quad (23.a)$$

Eq. (24) can be simplified by including Eq. (22.a) and Eq. (23.a) in which $\theta \rightarrow \theta/2$. Figure 2 shows the relationships between $\tilde{A}$ and $\tilde{B}$.

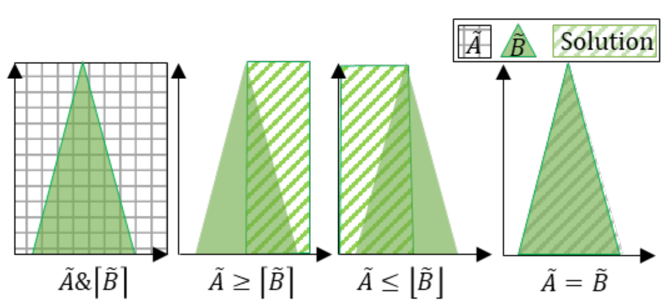

Figure 2. Relationships between $\tilde{A}$ and $\tilde{B}$.

5.2.1. *Validity, uncertain parameters, and results*

This paper applies the proposed robust approach to capture the uncertainty of four parameters, n_a, p, F, and S_λ. To build robust and resilient capability, managers focus on the upstream supply chain, a critical factor in supply chain management. Supply-side parameters (e.g., n_a, p, and F) considerably impact delivering value to customers, so these parameters are the focus of resilience management. For example, higher labor and food costs disrupt the U.S. restaurant supply chains (Cambon & Rubin, 2022). The manufacturing process (e.g., S_λ) is another major area, which has a considerable impact on supply chain performance in times of disruption.

This paper employs the proposed robust approach as follows: since p is in the first objective, p is replaced with $\mu(\tilde{p}x) + \omega\big(\sigma(\tilde{p}x)\big)$ in Eq. (1) of the proposed mathematical model. Note that x refers to $\sum_i \sum_j X_{ij} + \sum_i \sum_k X_{ik}$. To address the uncertain total supply capacity of raw material suppliers, F, Eq. (4) is replaced with Eq. (4a).

$$\sum_i \left(\sum_j X_{ij} + \sum_k X_{ik}\right) \geq \left(\theta\left(\frac{F^{I}+2F^{II}}{3}\right) + (1-\theta)\left(\frac{2F^{II}+F^{III}}{3}\right)\right) \tag{4a}$$

To address the uncertainty of manufacturers' material utilization, S_λ, Eq. (11) is replaced with Eq. (11a) and Eq. (11b).

$$\left((1-\theta/2)\left(\frac{S_j^{I}+2S_j^{II}}{3}\right) + (\theta/2)\left(\frac{2S_j^{II}+S_j^{III}}{3}\right)\right)\sum_i X_{ij} \geq \sum_w Y_{jw} \qquad \forall j \in J, \tag{11a}$$

$$\left((\theta/2)\left(\frac{S_j^{I}+2S_j^{II}}{3}\right) + (1-\theta/2)\left(\frac{2S_j^{II}+S_j^{III}}{3}\right)\right)\sum_i X_{ij} \leq \sum_w Y_{jw} \qquad \forall j \in J, \tag{11b}$$

Similarly, Eq. (12) is replaced with Eq. (12a) and Eq. (12b).

$$\left((1-\theta/2)\left(\frac{S_j^{I}+2S_j^{II}}{3}\right) + (\theta/2)\left(\frac{2S_j^{II}+S_j^{III}}{3}\right)\right)\sum_k X_{kl} \geq \sum_w Y_{lw} \qquad \forall l \in L, \tag{12a}$$

$$\left((\theta/2)\left(\frac{S_j^{I}+2S_j^{II}}{3}\right) + (1-\theta/2)\left(\frac{2S_j^{II}+S_j^{III}}{3}\right)\right)\sum_k X_{kl} \leq \sum_w Y_{lw} \qquad \forall l \in L, \tag{12b}$$

To address the uncertainty of employee availability in the residential area, n_a, Eq. (17) is replaced with Eq. (17a).

$$\sum_j P_{aj} + \sum_l P_{al} \leq \theta\left(\frac{n_a^{I}+2n_a^{II}}{3}\right) + (1-\theta)\left(\frac{2n_a^{II}+n_a^{III}}{3}\right) \qquad \forall a \in A, \tag{17a}$$

Note that the rest of the equations are the same as explained in the proposed mathematical model. To validate and verify the proposed robust approach, we compare the results with the original version of the method, which are shown in Table 3. The results confirm the reliability and validity of the proposed robust optimization, called the PFR method. The proposed robust method is moreover quicker than the original version, 27% quicker.

Table 3. Robust optimization results based scalarization method

#	Indices	Robust method (Babazadeh et al., 2017)		Proposed robust method		Improvement (%)	
	(a, i, j, k, l, r, w)	Z	Iteration	Z	Iteration	Z	Iteration
1	(2, 8, 2, 2, 2, 2, 2)	0.5962	216	0.5959	216	0.05	~0
2	(2, 10, 3, 3, 3, 2, 2)	0.3639	360	0.3635	360	0.11	~0
3	(3, 11, 4, 4, 4, 3, 3)	0.2853	227	0.2844	227	0.32	~0
4	(6, 20, 6, 6, 6, 5, 5)	0.5933	1924	0.5925	1024	0.13	46.8
5	(12, 20, 10, 10 ,10, 10, 10)	0.6176	109846	0.6168	53017	0.13	51.7
6	(13, 22, 14, 14, 14, 13, 13)	0.6454	80723	0.6446	73756	0.12	8.6
7	(14, 22, 16, 16, 16, 14, 14)	0.6482	111417	0.6473	40974	0.14	63.2
8	(14, 23, 17, 17, 17, 14, 14)	0.6339	742377	0.6331	353686	0.13	52.4
9	(15, 24, 18, 18, 18, 15, 15)	0.6415	83621	0.6405	58824	0.16	29.7
10	(15, 25, 20, 20, 20, 15, 15)	0.6543	2920198	0.6535	2363618	0.12	19.1

5.3. Proposed optimization algorithm: multiobjective dwarf-mongoose algorithm

To optimize a large-scale version of the proposed model, this paper develops a new evolutionary algorithm in computational intelligence (CI) based on a biological-based algorithm, called the dwarf-mongoose optimization algorithm (Agushaka et al., 2022). To optimize multiobjective problems, this paper develops the optimization algorithm presented by Agushaka et al. (2022). This paper extends their work by including a nondominated sorting concept in Pareto-based optimization techniques. We call the proposed algorithm the multiobjective dwarf-mongoose (MODW) algorithm. Dwarf-mongooses are diurnal-social mammals that are small predators of insects, scorpions, and small lizards. Their predators are snakes and bigger carnivorous mammals. Their behavior has attracted the attention of computational intelligence researchers. For example, mongoose groups do not completely trust a new immigrant at the beginning, but they accept the new immigrant in their group. However, after about five months, they return to normal behavior around the new member, treating it like any other member of the group (Gorman, 2017). Researchers have modeled dwarf-mongoose behavior into an optimization algorithm (e.g., dwarf-mongoose algorithm) (Agushaka et al., 2022). This paper contributes to the work presented by Agushaka et al. (2022) by developing their algorithm to include the nondominated sorting concept for solving multiobjective problems. MODW algorithm code is available here: www.GitHub.com/naricode/Data2023JCP. We refer the readers to Agushaka et al. (2022) for details of the algorithm.

Table 4. Validity of the proposed algorithm, MODW: Comparisons results with GAMS exact solver.

#	**Size**	**Indices** $(\boldsymbol{a}, \boldsymbol{i}, \boldsymbol{j}, \boldsymbol{k}, \boldsymbol{l}, \boldsymbol{r}, \boldsymbol{w})$	**Objective functions** **GAMS**	**Proposed algorithm**	**Time (second)** **GAMS**	**Proposed algorithm**
1	Small	(3, 13, 3, 4, 3, 2, 2)	Z_1=903494 Z_2=501 Z_3=176	Z_1=957034 Z_2=573 Z_3=167	9.41	618
2	Small	(4, 13, 5, 5, 5, 3, 4)	Z_1=903494 Z_2=501 Z_3=270	Z_1=1015645 Z_2=736 Z_3=98	9.52	604
3	Medium	(5, 14, 6, 6, 6, 3, 4)	Z_1=907039 Z_2=526 Z_3=324	Z_1=1013786 Z_2=773 Z_3=133	9.74	715
4	Medium	(6, 15, 7, 7, 7, 3, 4)	Z_1=1079130 Z_2=577 Z_3=378	Z_1=1090057 Z_2=1073 Z_3=236	9.83	604
5	Medium	(8, 16, 8, 8, 8, 3, 4)	Z_1=1082675 Z_2=602 Z_3=432	Z_1=1145572 Z_2=899 Z_3=229	10.36	602
6	Large	(20, 30, 25, 25, 25, 20, 20)	-	Z_1=1826896 Z_2=610 Z_3=1334	>3600	645
7	Large	(30, 50, 35, 35, 35, 30, 30)	-	Z_1=4850048 Z_2=1493 Z_3=2613	>3600	688
8	Large	(40, 70, 45, 45, 45, 40, 40)	-	Z_1=823576 Z_2=2473 Z_3=4018	>3600	862
9	Large	(50, 110, 55, 55, 55, 50, 50)	-	Z_1=13226795 Z_2=4159 Z_3=5959	>3600	1029

5.3.1. Validity of the proposed algorithm and results

The consistency of the obtained Pareto solutions shows the reliability of the proposed algorithm, MODW. To show the validity of the algorithm, the proposed algorithm's results are compared with an exact solver known as the general algebraic modeling system (GAMS).

As shown in Table 4, the proposed algorithm provides reliable solutions validated by the GAMS exact solver. While GAMS is unable to optimize large-scale problems, the proposed algorithm provides a set of optimal solutions. Figure 4 is an example of a set of Pareto solutions provided by the proposed algorithm.

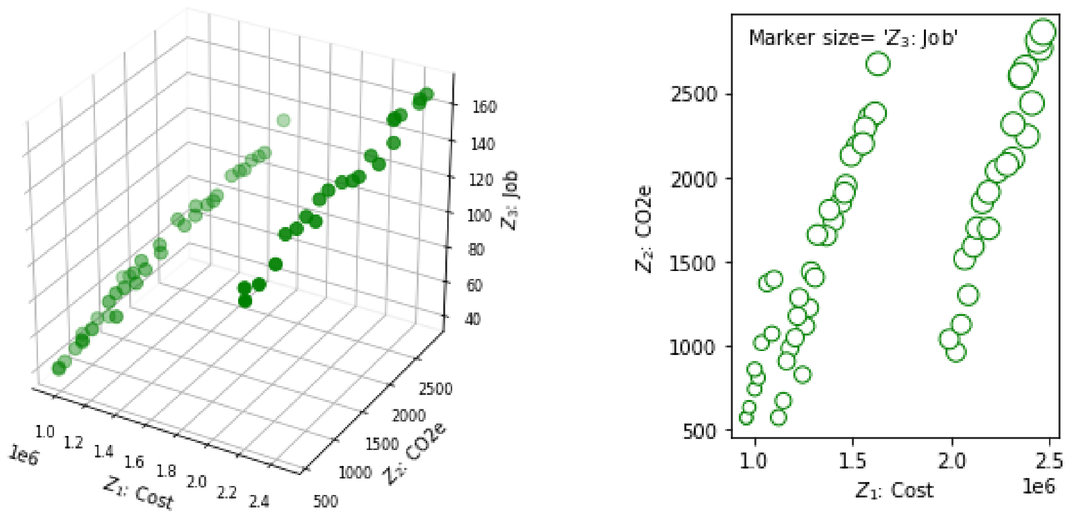

Figure 4. Pareto solution of example #1, ($a = 3, i = 13, j = 3, k = 4, l = 3, r = 2, w = 2$)

6. DISCUSSION AND CONCLUSION

Using a quantitative approach, this paper addressed the research question, "How can resilience and sustainability be included in decision-making models of logistics and supply chain management?" Logistics and supply chain problems involve several business partners that have conflicting objectives. To incorporate sustainable development goals into supply chain models, this paper suggested a multiobjective approach to include all three pillars of sustainable development, which were the economy, the environment, and society. Prior works recommended several objectives to follow these three pillars. Similar to past studies, this paper modeled not only costs, but also carbon dioxide equivalent (CO2e) in objective functions, which considered CO2e of employees' commuting miles (Boukherroub et al., 2015), manufacturing processes (Kalantari & Hosseininezhad, 2022), and transportation (Rezaei & Kheirkhah, 2018). To address the societal concerns of sustainable development, this paper included local employment (Boukherroub et al., 2015) and the number of jobs created (Pérez-Fortes et al., 2012; Rezaei & Kheirkhah, 2018).

To address the research question regarding resilience capability in supply chains, this paper included three concepts in the proposed supply chain model. First, this paper proposed a heterogeneous design for the supply chains in which members can have different capabilities. For example, in this paper, there were two types of manufacturers, large and small. The small manufacturers had the capability to change locations in between production periods. This capability can make a supply chain significantly more resilient in times of uncertainty. Small manufacturers' mobility also means they can accommodate small supply-order scheduling that cannot be addressed by a large manufacturer due to its high cost. Second, this paper included uncertain parameters in the model, which were discussed in Section 5.2. Addressing uncertainty can significantly improve supply chain resilience by decreasing the variance of outputs. Moreover, this paper proposed a new robust optimization approach, MODA in Section 5.3, which helps create resilience in supply chain decision-making models. This paper proposed a new algorithm to address complex large multiobjective supply chain problems. According to practice-based theory, sustainable supply chain resilience works as a practice to improve the overall performance of supply chains (Bromiley & Rau, 2014).

6.1. Managerial implication

Supply chain resilience is the current focus of managers due to its competitive advantages during disruptions. Moreover, public concerns encourage supply chain managers to include sustainable development goals in their decision-making models. This paper provided a decision-making model for a four-level supply chain consisting of raw material suppliers, intermodal hubs, heterogeneous manufacturers, and distribution centers. The proposed model included sustainable development goals in the objective functions while including resilience strategies in model inputs. Moreover, this paper provided an empirical evaluation of the proposed model to show its applicability. Using the proposed model, decision-makers of the proposed supply chains (e.g., cotton supply chain, glass recycle centers, olive oil supply chain, and biofuel supply chain) can simultaneously address supply chain resilience and sustainable development. Decision-makers can evaluate the social impacts of the proposed problem by looking at the social indicators presented in this paper. In other words, using the proposed model, decision-makers can select an option that has better social impacts (that is, job opportunities) rather than other options and alternatives. Simultaneously, decision-makers can consider CO2e generated in the model. Moreover, they can consider the carbon tax if there is an environmental regulation to control CO2e.

6.2. Limitations and future research

There are some limitations in this study, which can be addressed by future research. In terms of environmental impact, this research considered CO2e in the proposed supply chain model. A future study can develop this research to include other environmental issues such as air, water, and soil pollution. Social consideration in the proposed model was limited to job opportunities. Future research can model other social impacts such as slavery, health issues, illegal supply, equity, and inclusion. A future study can include other supply chain members in the proposed model, such as retailers and vendors. Last but not least, the proposed model can be developed to include multi-period and multi-product cases.

Appendix

A. Biofuel supply chain case data

Table A.1: Potential suppliers' locations

i	Country	Suppliers' names	locations
1	Clatsop County, Oregon	Arch Cape Creek	45°48'12.8"N 123°55'38.7"W
2		Coal Creek	45°48'08.7"N 123°52'38.3"W
3		Grassy Lake Creek	45°48'11.0"N 123°50'08.7"W
4		Necanicum Hwy	45°48'15.6"N 123°46'50.3"W
5		Lost Creek	45°48'06.7"N 123°43'14.7"W
6		Osweg Creek	45°50'57.4"N 123°32'15.2"W
7		Military Creek	45°48'54.6"N 123°29'21.2"W
8		Northrup Creek Rd	45°58'11.2"N 123°25'22.5"W
9		Cooperage Rd	46°01'22.9"N 123°37'30.5"W
10		California Barrel Rd	46°03'39.4"N 123°40'26.0"W
11		Palmer Rd	46°06'24.0"N 123°44'15.0"W
12		Nehalem	46°04'58.8"N 123°41'33.6"W
13		Neverstill Rd	45°59'33.2"N 123°20'04.7"W
14		Sunset	45°54'13.2"N 123°51'14.8"W
15	Columbia County, Oregon	Wallace Rd	45°59'37.7"N 123°16'32.7"W
16		Mist	46°01'05.0"N 123°14'44.0"W
17		Lindgren	46°01'54.1"N 123°14'50.1"W
18		Fall	46°04'58.2"N 123°15'29.1"W
19		Black	45°56'27.2"N 123°10'17.7"W
20		Pittsburg	45°54'04.5"N 123°08'26.5"W
21		McDonald	45°47'38.5"N 123°13'01.4"W
22		Columbia F	45°52'02.5"N 123°07'06.4"W
23		Scappoose	45°50'04.9"N 123°00'40.1"W
24		Clatskanie	46°00'28.1"N 123°02'42.1"W
25	Tillamook County, Oregon	Gravel	45°44'29.2"N 123°49'37.0"W
26		Wheeler	45°41'29.6"N 123°51'48.1"W
27		Foley	45°35'02.5"N 123°51'41.7"W
28		Berry	45°32'32.4"N 123°40'46.2"W
29		Ben	45°35'13.3"N 123°31'55.3"W
30		Rutherford	45°36'34.6"N 123°24'01.4"W
31		Jackson	45°16'56.2"N 123°49'10.3"W
32		Three Rivers	45°11'53.7"N 123°49'51.9"W
33		Oretown	45°08'54.2"N 123°57'27.2"W
34		Fb 8n	45°38'41.0"N 123°38'53.4"W
35		South Fork	45°21'20.7"N 123°37'11.2"W
36	Washington County, Oregon	West Fork	45°42'55.0"N 123°11'56.7"W
37		West Fork Dairy	45°42'11.6"N 123°12'11.2"W
38		Wilson River	45°38'56.1"N 123°19'31.5"W
39		Sylvia	45°31'59.4"N 123°11'25.6"W
40		Stimson	45°31'25.9"N 123°21'27.5"W
41		William Rd	45°29'30.4"N 123°24'56.0"W
42		SW Summit	45°28'06.9"N 123°16'02.8"W
43		Panther	45°44'49.1"N 123°03'45.8"W

Table A.2: Potential intermodal hubs' locations

k	County	Names	Locations
1	Clatsop County, Oregon	Necanicum	45°47'22.1"N 123°49'04.7"W
2	Clatsop County, Oregon	Fish	45°55'24.1"N 123°29'33.1"W
3	Columbia County, Oregon	Neha	45°59'05.3"N 123°14'45.5"W
4	Columbia County, Oregon	Pit	45°54'27.2"N 123°07'53.3"W
5	Tillamook County, Oregon	Cedar	45°21'10.3"N 123°48'37.3"W
6	Tillamook County, Oregon	Minich	45°35'23.6"N 123°52'25.3"W
7	Tillamook County, Oregon	Wilson	45°34'57.8"N 123°33'09.3"W
8	Washington County, Oregon	Howell	45°34'11.4"N 123°11'56.8"W
9	Washington County, Oregon	West Fork	45°41'09.9"N 123°11'48.3"W

Table A.3: Potential small manufacturers' locations

j	County	Names	Locations
1	Clatsop County, Oregon	North Fork	45°47'49.9"N 123°49'01.5"W
2	Clatsop County, Oregon	Nehalem	46°03'48.6"N 123°41'19.9"W
3	Columbia County, Oregon	Nehalem HN	45°59'35.7"N 123°15'20.8"W
4	Columbia County, Oregon	Timber Rd	45°50'27.0"N 123°12'55.0"W
5	Tillamook County, Oregon	Fir	45°20'51.6"N 123°48'56.7"W
6	Tillamook County, Oregon	Foley	45°37'21.0"N 123°51'22.7"W
7	Washington County, Oregon	Wilson	45°36'38.9"N 123°14'29.2"W

Table A.4: Potential large manufacturers' locations

l	County	Names	Locations
1	Clatsop County, Oregon	Fishhawk	45°56'31.2"N 123°32'04.8"W
2	Columbia County, Oregon	Nehalem	45°55'13.7"N 123°08'25.0"W
3	Tillamook County, Oregon	Wilson	45°27'57.0"N 123°45'47.8"W
4	Washington County, Oregon	Dandy	45°39'09.7"N 123°08'40.9"W

Table A.5: Potential warehouses' locations

State	Names	Location
Oregon	Warehouse 01	45°32'52.1"N 122°56'53.5"W
Oregon	Warehouse 02	45°31'11.3"N 123°02'02.2"W
Washington	Warehouse 03	45°48'31.6"N 122°40'09.5"W
Washington	Warehouse 04	45°54'45.9"N 122°45'09.6"W

B. The MODW algorithm's rate of convergence

Regarding the computation time, the proposed MODW algorithm is quicker than the three other metaheuristic algorithms. This paper optimizes three common multiobjective test problems and compares results with three other algorithms. Table A.6 shows the test problems used in this paper to compare the proposed algorithm's results with three common algorithms in prior studies. This paper uses the same values for tuning algorithms' parameters (e.g., iteration=100, population=50, Pareto solutions = 100). Other parameters' values are the proposed algorithm (babysitter=3 and peep=2), multiobjective evolutionary algorithm based on decomposition (MOEA-D) (the weight vectors=20), Pareto envelope-based selection algorithm-II (PESA-II) (grid size=10 and Inflation=0.1), and strength Pareto evolutionary algorithm-II (SPEA-II) (crossover = 0.7 and mutation = 0.2). Table A.7 shows that the proposed algorithm has a reasonable computation time rather than the other three algorithms. Thus, the proposed algorithm has an acceptable rate of convergence.

Table A.6. Multiobjective test problems (MOTP)

Minimization objectives	Constraints
Min MOTP01 (Zitzler et al., 2000, p. 177): $f_1(x) = x_1$ $f_2(x, g(x)) = g(x)(1 - (f_1/g(x))^{0.5})$ $g(x) = 1 + 9(n-1)^{-1}\sum_{i=2}^{n} x_i$	$0 \leq x_{i\in n} \leq 1$ $n = 3$
Min MOTP02 (Fonseca & Fleming, 1995, p. 8): $f_1(x) = 1 - \exp\left(-\sum_{i=1}^{n}\left(x_i - 1/\sqrt{n}\right)^2\right)$ $f_2(x) = 1 - \exp\left(-\sum_{i=i+1}^{n}\left(x_i + 1/\sqrt{n}\right)^2\right)$	$-4 \leq x_{i\in n} \leq 4$ $n = 3$
Min MOTP03 (Kursawe, 1991, p. 196): $f_1(x) = \sum_{i=1}^{n-1}\left(-10\exp(-0.2(x_i^2 + x_{i+1}^2)^{0.5})\right)$ $f_2(x) = \sum_{i=1}^{n}(\lvert x_i\rvert^{0.8} + 5\sin(x_i)^3)$	$-5 \leq x_{i\in n} \leq 5$ $n = 3$

Table A.7. Comparisons of multiobjective optimization algorithms

Problem	Time (second)	Algorithm
MOTP01	50	The proposed algorithm, MODW
MOTP02	20	
MOTP03	16	
MOTP01	51	PESA-II
MOTP02	37	
MOTP03	32	
MOTP01	24	MOEA-D
MOTP02	26	
MOTP03	19	
MOTP01	29	SPEA-II
MOTP02	30	
MOTP03	29	

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