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ORIGINAL ARTICLE

Metaheuristic optimizers to solve multi-echelon sustainable fresh seafood supply chain network design problem: A case of shrimp products

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Abstract Seafood products are sought-after among communities all over the globe and are the main sources of essential nutrition for humans. Recently, the seafood supply chain networks have encountered obstacles that new sustainability regulations and the pandemic have brought forward. In this study, a novel supply chain network is developed for fresh seafood, considering sustainability aspects, to ideally balance the financial aspect of the network while enhancing the recycling of waste products. Moreover, four metaheuristics are employed to conquer the computational complexity of exact solution methods. To evaluate the performance of the algorithms in addressing the complexity of the proposed seafood supply chain model, some numerical examples in three different scales are designed. The obtained results from metaheuristic optimizers are assessed based on five effective measures. To facilitate the statistical analysis process, each measure is normalized using the relative deviation index indicator. According to the results obtained from the implementation of metaheuristic algorithms, it can be concluded that the multi-objective grey wolf and multi-objective golden eagle optimizers outperform the other two solution methods in terms of quality of solutions. Therefore, they can be applied efficiently in solving real-world seafood supply chain network problems.

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1. Introduction

In recent decades, urbanization has been attributed as a dominant and universal phenomenon in developing tight competition in the market of agricultural and food products (also known as agri-food) [1–3]. The most indispensable goals or missions of present businesses and industries to uphold and improve their competitive advantages are increasing the satisfaction level of customers, responding to the demands, delivering products with admirable quality in the shortest time, and finally fortifying their potential capabilities [4]. Seafood is counted as one of the most enriched nutritional intakes owing to its high level of minerals, protein, and vitamins. Also, seafood production industries have experienced a steady increase in the amount of captured and farmed seafood products during the past five decades [5,6]. Accordingly, Asian and European countries have recorded continuous growth in seafood production during the past decades, as shown in Fig. 1. As a result of excessive pressure on the related industries and businesses, this trend reflects an increasingly insistent demand from the seafood products market.

Seafood's burgeoning demand and its saturated market have led active organizations and firms to seek potential solutions to this problem [7]. It is commonly understood that supply chain network design (SCND) refers to the development of reliable solutions for the seafood industry to control the market by timely transport of seafood products within domestic and international networks at the lowest possible cost. A supply chain is comparable to a huge system of systems in which multiple constituent systems (*i.e.,* the involved entities in the chain) collaborate to achieve a higher-level set of goals for the chain as a whole [8]. Correspondingly, it can be reckoned that the more well-structured and detailed supply chain networks in a specific industry, the higher customer satisfaction and competitive advantages.

Considering the current complex market situation and the fierce competition among the seafood network components, stakeholders and policymakers have paid attention to reverse flows within the supply chain networks. They realized that the reverse flow of products, reusing, recycling, and reprocessing of used or imperfect commodities can lead to more added value for the products, despite the additional complexity of the problem and extra expenses that can be imposed on the system [9]. In this matter, the combination of conventional SCND with the reverse flow supply chain defines a new concept, namely a closed-loop supply chain network (CLSCN).

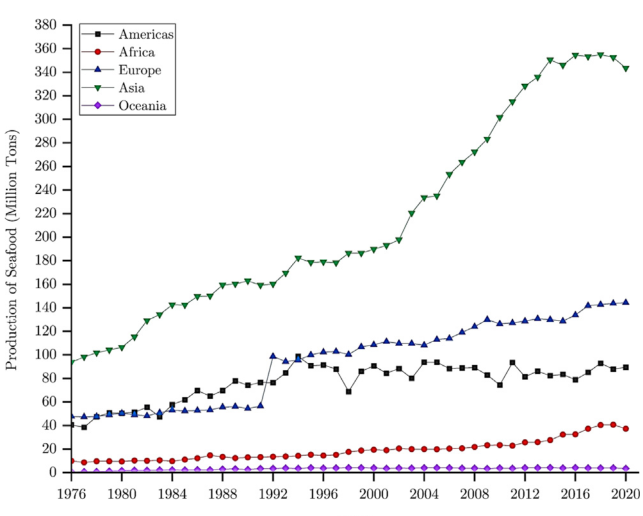


Fig. 1 Seafood production trend during the last decades (FAOSTAT: Fisheries(https://www.fao.org/fishery/statistics-query/en/home)).

In the current industrial environment and businesses, the strategies, goals, and missions are envisioned in compliance with sustainability practices [10]. Although the consideration of sustainability development goals in all operations of companies can be extremely costly, particularly in supply chain related activities, it considerably enhances the profitability of organizations and the loyalty of customers [11]. Additionally, sustainability practices emphasize the financial, social, and environmental aspects of an operation and assist human beings in preserving their natural surroundings while benefiting from the business activities of a company or industry.

In this work, a multi-echelon seafood supply chain network is conceptualized and customized for shrimp industries and markets to investigate the compatibility of the optimization model in real-world settings. To be more specific, the multi-echelon network embraces the key components of the seafood market, including the commercial fisheries, shrimp farms, distribution centers, processing factories, and market for the forward flow of goods, in addition to a set of waste processing units which are designed to cover the backward or reverse flow of network in other industries, such as food, agricultural, medical/pharmaceutical, and paper/textile products.

The seafood production and processing activities contribute to environmental and social issues, such as water pollution, gas emissions, and human health risk. The seafood markets and industries transfer the solid waste to the surrounding landfills or discard a significant amount of waste materials to the sea or coastal areas in and around it. Seafood waste materials which are not buried degrade quickly, and consequently, the anaerobic digestion of organic matter leads to the emission of greenhouse gases (*e.g.*, carbon dioxide, methane) and other pollutant gases that cause climate change (*e.g.*, amines, ammonia (NH_3), hydrogen sulfide (H_2S)) [12].

According to the Environmental Protection Agency (EPA) of the United States, dumping of fish wastes into ocean waters can cause major environmental issues, such as suffocation or burial of living organisms, and reduction of oxygen levels in the seawater at the ocean bottom [13]. Moreover, the leakage of seafood effluents in landfills or other disposal areas can cause the contamination of groundwater, coastal water, and natural ecosystems which adversely affects human health by releasing the suspended solids, disinfectants, and coliform bacteria from the seafood waste leachate [14]. In addition, the unpleasant and obnoxious odors are released during the decomposition of seafood products can cause nausea, sickness, or stress for people in affected areas, as one of its social issues [15]. Thus, it can be argued that the increase of seafood waste materials in the supply network can significantly affect the sustainability of the system from both environmental and social features.

In addition to the economic pillar of sustainability, this study incorporates the environmental and social aspects of the supply system aiming to simultaneously improve the efficiency and performance of the seafood market and assist the industry with its environmental and social responsibilities. The proposed seafood supply chain network has two principal objectives: (I) Reinforcing the supply network to be operated at the lowest cost; (II) Efficient management of the generated waste throughout the network at the highest possible rate for diminishing the environmental issues and social disturbance originates from the seafood waste, especially in the vicinity of the markets.

This research makes substantial contributions to the seafood supply chain literature by focusing on sustainability factors and incorporating a variety of waste processing factories in different markets and industries. Designing a multi-objective mathematical model, in which the economic, environmental, and social aspects of a multi-echelon seafood supply network are effectively considered as an integrated framework, can both enhance the operational performance of the existing system and mitigate some of the most challenging issues. Thus, this paper seeks to assist decision-makers and managers in the shrimp markets and industries by finding reasonable answers to the following principal questions:

- What is the optimal total cost imposed on the elements of the supply network in satisfying the needs of end customers?
- What is the optimal set of potential locations for the establishment of distribution centers considering the distance between the potential centers and the shrimp suppliers, processing factories, retailers, and waste processing plants in the supply network?
- What is the required quantity of fresh shrimps that should be supplied from commercial fisheries and shrimp farms to meet the demands of all customers while avoiding the excessive flow of shrimp which negatively affect the sustainability of the system?
- Which solution approach(es) can be applied in addressing the complexity of real-world problems while providing a good quality solution?

To answer the last research question, a set of single-solution and population-based metaheuristic optimizers are utilized to conquer the NP-hardness of the problem and consequently determine the most efficient solution method(s), compatible with this problem.

The rest of the paper is devoted to the following sections. The research studies conducted in the sustainable supply chains, agri-food, and seafood supply chain literature are reviewed and summarized in Section 2. Then, a novel seafood supply chain structure focusing on the shrimp industry is mathematically formulated in Section 3. In Section 4, the metaheuristic optimizers and the encoding strategy are clarified. The practical analysis, problem frameworks, and performance measures for the metaheuristic solution methods are rendered in Section 5. The outputs of the metaheuristic optimizers in the experimental examples and the sensitivity analysis on the behavior of the optimization model are presented in Section 6. Section 7 provides some managerial insights based on the findings and output of this research study. Finally, Section 8 expounds on the conclusions and proposes some avenues for further research.

2. Literature review

At this point, a broad survey is conducted on sustainable supply chain networks, agri-food, and seafood supply chain networks (SCNs) in various circumstances, as summarized in Table 1.

2.1. Sustainable supply chain network

In this sub-section, some of the recent studies on sustainable SCNs are reviewed. It is noteworthy to mention that different dimensions of sustainable SCNs have been investigated and discussed in previous studies. Furthermore, numerous comprehensive studies have scrutinized the literature on the sustainable SCNs such as Shekarian *et al.* (2022) [16], Khan *et al.* (2021) [17], Koberg and Longoni (2019) [18], and Ansari and Kant (2017) [19]. A concise review of sustainable SCNs is rendered as follows.

Forghani *et al.* (2023) developed a hydrogen supply chain network as a two-stage mathematical model to cope with the production and inventory decisions. The model determines the optimal channel and quantity for the distribution of hydrogen empowered by location data which is obtained from a computer application. Additionally, the model aims to respond to the demands while controlling the emissions and minimizing the total cost [20]. Ahmed et al. (2023) propounded a multi-tier sustainable SCND problem for tire production industries. The problem is framed as a mathematical model considering several recovery opportunities [21]. Rabbani *et al.*, (2022) outlined the phosphorus supply chain as mathematical programming and considered sustainability aspects to prevent harmful environmental and social impacts of phosphorus. They designed a risk-averse model to control the uncertainty of demand and supply within the network [22]. Sadjady Naeeni and Sabbaghi (2022) focused on the glass industries and developed an optimization model to adjust the SCN from a sustainability standpoint. To this end, a multi-objective model monitors three dimensions of the sustainable network including the total cost of the network, dangerous emissions, and social responsibility [23].

Eghbali *et al* (2022) conceptualized a reward-penalty concept in a sustainable SCN, as well as the source separation, to manage the urban solid waste. The problem was formulated as a multi-objective framework to concurrently balance the financial aspects of the network, emissions, and destructive ecological impacts of wastes [24]. Lahri *et al.*, (2021) mathematically framed a sustainable SCND to financially calibrate the network while the environmental and social targets are optimized. The model introduces the optimal location of facilities and the flow of products between the network's components. The raised model was solved in two steps: firstly, the weight of each green supplier is identified and then the SCND problem is solved using the obtained weights [25]. Fragoso and Figueira (2021) concentrated on the wine industry and suggested a sustainable supply chain model for the Portuguese southern territory. Simultaneous control of profitability, emission and water consumption, and the employment within the SCDN are the three pillars of the proposed model. Furthermore, the model attempts to handle the capacity, production, and allocation decisions for the wine industry [26].

Table 1 Literature review.

	References	Model Setting							Methodology				Sustainability Concepts			Objective Function	Type of Product
		LP	NLP	IP	MILP	MINLP	SO	MO	E	H	MH	Sim	Eco	Env	S		
Agri-food Supply Chain	[35]				✓			✓	✓				✓	✓	✓	C, S, UG, PC	Vegetable
	[36]	✓							✓				✓			R	Crops
	[37]		✓				✓		✓				✓			HR	Crops
	[38]				✓		✓		✓				✓			C	Plants and trees
	[39]	✓					✓		✓				✓			C	Food
	[40]				✓		✓		✓				✓			C	Wine grape
	[45]				✓		✓		✓				✓			C	Food
	[42]				✓		✓		✓				✓			Income	Tomato
	[44]				✓		✓		✓				✓			R	Crop
	[43]				✓		✓		✓				✓			R	Pepper
	[46]		✓					✓				✓	✓			R, PV	Fruits
	[47]				✓			✓	✓				✓	✓		C, EI	Mushroom
	[48]				✓		✓		✓				✓			C	Food
	[49]				✓		✓		✓				✓			C	Crop residue
	[50]				✓			✓			✓		✓		✓	C, S	Citrus
	[51]				✓		✓				✓		✓			C	Rice
	[63]		✓				✓		✓				✓			R	Agricultural products
	[52]		✓				✓		✓				✓			R	Agricultural products
	[64]				✓			✓	✓			✓	✓	✓	✓	C, EI, J	Wheat
	[53]				✓		✓				✓		✓			C	Sugarcane
	[54]				✓			✓			✓		✓	✓		C, EI	Date
	[55]		✓				✓				✓		✓			C	Agricultural products
	[56]				✓		✓				✓		✓			C	Walnut
	[57]				✓			✓	✓				✓	✓		C, EI	Pistachio
	[58]				✓			✓	✓				✓	✓	✓	C, EI, CU	Food
	[59]	✓						✓			✓		✓	✓	✓	C, EI, J	Olive
	[60]					✓		✓	✓				✓		✓	C, J	Avocado
	[65]					✓	✓				✓		✓			C	Sugarcane by-product
	[66]					✓		✓			✓		✓	✓	✓	C, EI	Sugarcane
	[1]					✓		✓			✓		✓	✓	✓	C, EI, P, EI	Agri-food products
	[61]					✓		✓		✓	✓		✓			C, TM	Vegetable
	[62]				✓			✓			✓		✓		✓	C, FR, NV	Food bank
Seafood Supply Chain	[67]	✓					✓		✓				✓			R	Farmed fish
	[68]	✓					✓		✓				✓			R	Farmed Atlantic salmon
	[69]	✓					✓		✓				✓			R	White sturgeon
	[70]	✓					✓		✓				✓			R	Shrimp
	[71]			✓			✓		✓				✓			E	Salmon
	[72]				✓		✓		✓				✓			P	Salmon
	[73]	✓					✓		✓				✓			R	Fish (Fisheries)
	[74]		✓				✓				✓		✓			R	Warm-water fish
	[75]				✓			✓	✓	✓			✓		✓	C, S	Fish
	[76]				✓			✓		✓			✓		✓	C, S	Fish
	[77]				✓		✓				✓		✓			C	Shrimp

Table 1 (*continued*)

References	Model Setting							Methodology				Sustainability Concepts			Objective Function	Type of Product
	LP	NLP	IP	MILP	MINLP	SO	MO	E	H	MH	Sim	Eco	Env	S		
[78]				✓		✓		✓		✓		✓	✓		C	Fish
This Study				✓			✓			✓		✓	✓	✓	C, W	Seafood (Shrimp)

"LP: Linear programming; NLP: Non-linear Programming; IP: Integer Programming; MILP: Mixed Integer Linear Programming; MINLP: Mixed Integer Non-Linear Programming; Eco: Economic; Env: Environmental; S: Social; SO: Single Objective; MO: Multi-Objective; R = Profit/revenue; C = Cost; S: Satisfaction; W: Waste recycling/usage; E: Equipment management such as fishing net; P: Production; EI: Environmental impacts; J: Job opportunities; CU: Capacity utilization; UG: Use of the growing area; PC: Production capacity; HR: Harvesting risk; PV: Price variation; TM: Time; E: Exact; H: Heuristics; MH: Metaheuristics; Sim: Simulation;.".

Rabbani *et al.*, (2020) constructed an optimization model for the location-allocation decisions within SCN following the sustainability regulations. They tried to consider different technologies and emissions for both transportation and facilities of the network. Moreover, back-ordering and customer dissatisfaction are assumed to be the social impacts of the network. Finally, they reinforced the model using a robust optimization method and utilized an improved augmented ϵ-constraint method to obtain non-dominated solutions [27]. Kaboli Chalmardi and Camacho-Vallejob (2019) modeled a sustainable SCND as a bi-level optimization framework. In the proposed model, the upper level or decision maker is in charge of monitoring the environmental policies, and the lower level or follower is the manager of the supply chain. At the upper level, decision-making inclines toward environmental objectives while at the lower level controlling financial aspects is of importance. In the model, subsidies are considered as a financial motivation for managers in order to implement eco-friendly technologies. Due to the incapability of the exact methods in solving the problem, a metaheuristic-based approach was utilized [28].

Yadav *et al.*, (2018) offered a mathematical model for multiple-channel settings containing sustainable objectives, including the optimization of total network cost and the emission reduction throughout the system. The online and local distribution systems were embedded in an uncertain environment. The results assert that the multiple-channel setting economically and environmentally outperforms the traditional supply chain networks [29]. Zhang et al., (2016) integrated the multiple distribution channels concept into an optimization model to directly deliver the products to customers from existing establishments. The proposed model encompasses sustainability ideas such as total cost reduction, delivery coverages, and green practices. They chose to solve the model using metaheuristic algorithms and enhanced artificial bee colony by conducting a novel encoding scheme. Finally, several numerical examples were used to probe the validity of the model [30].

2.2. Agri-food supply chain network design

First, a well-chosen selection of existing studies dealing with Agri-Food Supply Chain (AFSC) problems is briefly discussed below. In the literature, some cutting-edge approaches in classifying and gathering agri-food products (*i.e.*, vegetables, farm animals' products, fruits, and crops) stated by Routroy and Behera (2016) [31], Luo *et al.* (2018) [32], Kamble *et al.* (2020) [33] and De and Singh (2021) [34], in addition to their modeling techniques. Also, this section explicates the frameworks and approaches of studies.

In one of the first studies, Van Berlo (1993) developed a supply chain model for optimizing the vegetable product growth, gathering, processing, and marketing [35]. Jolayemi (1996) introduced a methodology to optimize the profits and planning time intervals in harvesting agricultural products, in which the best quantity and location of products are determined [36]. Also, a non-linear optimization scheme was outlined by Allen and Schuster (2004) for reducing waste in the manufacturing processes by predicting the investment and harvest requirements in a wine grapes farm. The main factors considered by the model were storage capacities, climate risk assessment, and harvesting [37]. Rantala (2004) introduced an AFSC model for distributing plantlets. The model focused on improving production costs and customer satisfaction simultaneously [38]. An SCN for chickpea-oriented productions was pioneered by Apaiah and Hendrix (2005), including all detailed and effective players in SCN. The model aimed to decrease the network costs considering the customer satisfaction and capacity of plants [39]. In another work, Ferrer *et al.* (2008) introduced a crop supply chain to keep track of the harvesting, transportation, production, and packing of agricultural products in each period [40]. In generating agricultural biofuel, a model was developed by Ekşioğlu *et al.* (2009) and solved using CPLEX. The results proved that the shipping costs, storing, and producing biofuel were at their optimum [41].

Ahumada & Villalobos (2011) and Ahumada *et al.* (2012) respectively concentrated on the production and planning process of tomatoes and red pepper on farms [42,43]. Particular subjects like planning for employing laborers and water use were investigated in preceding papers. Ahumada & Villalobos (2011) also endeavored to boom the profitability of agricultural industries considering the quality of the harvest [44]. Rong *et al.* (2011) focused on the highest-quality agricultural products across the supply chain [45]. Teimoury *et al.* (2013) investigated the AFSC of farming, distributing, and retailing activities. They introduced a system analysis technique for analyzing the behavior of the network and evaluating the interaction between different elements [46]. In recent literature, fewer studies have been conducted to address the issues of AFSC problems. Banasik *et al*. (2018) designed a CLSCN for the mushroom market and then introduced a method to analyze the proposed optimization model based on prior studies [47]. In another study, Aras and Ümit (2018) presented a robust model for the food supply chain network considering uncertainty of demand [48].

Furthermore, a considerable number of published papers in AFSC literature focused on finding the best location of facilities. In one of these studies, Sarker *et al*. (2018) assessed a multi-hub network to find the best location for establishing storage facilities in farmland [49]. Cheraghalipour *et al*. (2018) focused on optimizing the total cost and customer satisfaction level in the citrus CLSCN [50]. In another study, Cheraghalipour *et al*. (2019) studied the Iranian rice and its by-product industry to control the network at the lowest total costs [51]. Yan *et al*. (2020) investigated the supply chain of fresh agricultural goods, considering income-sharing contracts, and then proposed a new heuristic method to enhance the transportation system [52]. Chouhan *et al*. (2021) designed a CLSCN model for the Indian sugarcane business and applied metaheuristic algorithms to optimize the total network cost [53]. Hamdi-Asl *et al*. (2021) conceptualized a sustainable date SCN considering its special features and comprehensive industries arrangement in the network [54]. Wang *et al*. (2021) explored a bi-level optimization model for fresh agricultural products to establish distribution centers in potential locations, and then applied a case study to validate the applicability of the model [55].

Salehi-Amiri *et al*. (2021) proposed a CLSCN for agricultural products by concentrating on the walnut market and industry [56]. Moreover, the pistachio supply chain was investigated by Gilani and Sahebi (2021), considering sustainability goals (*e.g*., CO_2 emission) [57]. Foroozesh *et al*. (2022) formulated a multi-objective linear model for a food SCN to deal with the restrictions on the capacity of the plants, transportation expenses, costumers demand, and carbon dioxide emission [58]. Seydanlou *et al*. (2022) designed a CLSCN for the Iranian olive industry, considering three pillars of sustainability, to improve the location, assignment, and inventory-related decisions [59]. Salehi-Amiri *et al*. (2022) implemented a model for the Mexican avocado business taking into account the employment opportunities [60]. Kommadath *et al*. (2023) structured a mathematical model to run the vegetable business with the lowest cost and at optimal scheduling. Also, they employed heuristic and metaheuristic approaches to obtain the solution [61]. Finally, Ghahremani-Nahr *et al*. (2023) conceptualized the food bank network, as an optimization framework, to retain the freshness of food and increase its nutritional value at the lowest cost [62].

2.3. Seafood supply chain network design

In the literature, it can be found that a few number of papers have studied the fresh seafood supply chain network (SFSCN) problems, particularly shrimp SCN. Here, we concisely review the state-of-the-art works on SFSCN.

In one of the earliest studies, Forsberg (1996) proposed an optimization model for aquacultures to improve the fish production [67]. Thereafter, Forsberg (1999) explored the effective factors on fish growth in order to guarantee a higher amount of production for aquacultured Atlantic salmon [68]. In order to cover various management standpoints concerning white sturgeon caviar production, Sanders *et al*. (2003) developed an optimization model to record a higher yield [69]. Yu *et al*. (2009) formulated a model to enhance the partial harvesting of shrimp [70]. Cisternas *et al*. (2013) preseneted a linear model to examine the resource usage and financial aspects of aquacultures. The obtained results revealed almost one-fifth reduction in the maintenance cost and an increase in other benefits in the largest salmon farms in Chile [71]. Bravo *et al*. (2013) constructed a linear optimization model to pursue higher production performance considering biological and health concerns in salmon farms [72]. Bakhrankova *et al*. (2014) modeled production planning in the fish SCN considering the supply and demand uncertainties [73].

Tabrizi *et al*. (2018) conducted a study on the SFSCN for aquacultured warm-water fishes. The proposed network was solved using a modified particle swarm metaheuristic [74]. In 2021, Fasihi *et al*. formulated two different SFSCNs for fish, considering three aspects of a sustainable network [75,76]. Besides implementing an exact solution method, they used metaheuristic optimizers to solve the large-sized problems. Mosallanezhad *et al*. (2021) constructed a single-objective structure to manage a shrimp supply chain network financially [77]. Finally, Purnomo *et al*. (2022) designed a comprehensive CLSCN for fish production in order to preserve the traceability and environmental-friendliness of the network [78].

Based on the reviewed papers in the literature, it is evident that a limited portion of supply chain studies belonged to the SFSCN. In addition, implementing the reverse flow in the SFSCN field is noticeably limited. Accordingly, there is a need for much more research on this area, especially in the shrimp supply chain network.

2.4. Research gaps

Based on the reviewed papers in previous sub-sections, some research gaps are discussed below. In the literature, there is a lack of a comprehensive optimization model for seafood products considering the waste or returned materials and sustainability dimensions. As aforementioned, the previous studies and reports stated that the seafood waste can result in several human health and environmental issues. However, in the SFSCN literature, there is no research concentrating on the seafood waste reduction or the maximization of waste usage within the network.

As shown in Table 1, a few studies have drawn attention to the seafood supply chain design and most of them have considered sustainability aspects of the supply chain in an imperfect manner. Furthermore, there are demands for seafood waste in the real world from a variety of industries, such as food, agricultural, cosmetics, and paper processing factories. Indeed, the satisfaction of demands placed by the relevant industries must be considered in designing a reliable and consistent network with respect to real-world systems.

In this study, these research gaps are addressed by developing a multi-echelon supply chain network in the form of a multi-objective multi-commodity mathematical model, which aims to enhance the system by balancing the total network costs at the lowest possible amount and simultaneously increasing the waste usage within the network at the highest volume. Also, a comprehensive research has been conducted to identify the major actors in the real seafood supply chain network (*i.e.,* commercial fisheries and farms, to distribution centers, retailers, and waste processing plants). The proposed model contains forward and backward flows of commodities between different stages of the network.

3. Optimization model

Here, prior to presenting the optimization model of the problem under study, the description and main assumptions of the problem are provided as follows.

3.1. Model definition

In this sub-section, a multi-echelon supply chain network is designed for shrimp to satisfy the needs of end customers and other related industries in the network. The framework of the proposed multi-echelon shrimp supply chain (MESSC) network is illustrated in Fig. 2.

Shrimp is a valuable seafood supplied by either commercial fishing or shrimp farming that focuses on aquaculture activities to grow high-quality shrimp for human consumption. In the next level of the network, the wholesalers, also known as distributors, purchase the caught or harvested shrimps in the first level and transport them to their distribution centers for selling to retailers or processing factories. Based on their inventory and capacity, each distribution center tries to satisfy demands of customers, retailers, and/or processing factories. The retailers sell the fresh shrimp purchased directly from wholesalers to the end consumers. However, the shrimp purchased by factories are processed as frozen and canned products before being sold through their distribution channels to retailers, hypermarkets, and other customers. Shrimp is processed in factories by removing its solid wastes (*e.g.,* the head, shell, and tail portions) which constitute 45 to 60 percent of the original shrimp weight [79].

Moreover, the large amounts of fresh shrimp which wholesalers sell are wasted during the distribution operations due to the highly perishable feature. On the other hand, the

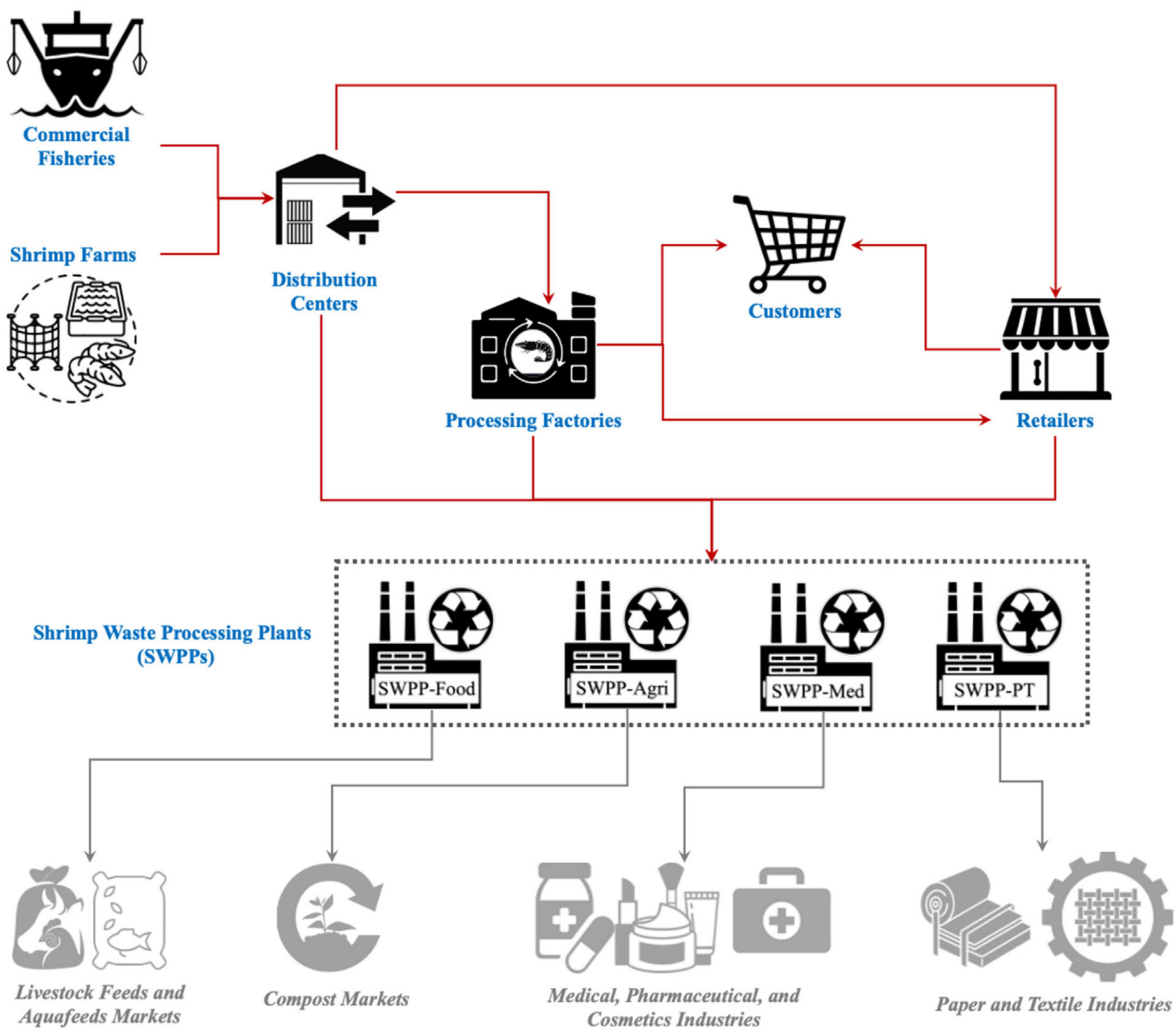


Fig. 2 The multi-echelon shrimp supply chain network.

proper processing of shrimp wastes is of great importance since they contain several bioactive compounds (*e.g.,* chitin, pigments, amino acids, and fatty acids) which have large-scale applications in different industries, such as pharmaceutical, agricultural, food, cosmetic, paper, and textile [79]. In addition, improper management of accumulated biowastes can lead to severe environmental violence. Hence, the produced shrimp wastes can be transported to various shrimp waste processing plants (SWPPs) with different applications, which possess a key position in recovering biomaterials from shrimp waste materials and maintaining related environmental impacts.

In the proposed MESSC network, the shrimp waste is shipped from distribution centers, retailers, and processing factories to four different SWPPs with distinct applications. The shrimp waste can be processed in SWPP-Food processing factories to produce the supplements and additives of livestock feeds and aquafeeds which refer to any feed given to cattle, poultry, and aquatic farmed animals. The next type of waste processing factory, SWPP-Agri, focuses on agricultural applications of shrimp waste. The target of these factories is to produce natural compost from shrimp heads, tails, and shells, as rich sources of chitin and chitosan and use them as plant fertilizer. In addition, chitin can be used as an ingredient in several cosmetics products (*e.g.,* nail polish, shampoo, make-up powder, and creams) and also has various applications in human medicine as an active constituent (*e.g.*, wound care bandages and dressings, antibacterial sponges, and contact lenses). The SWPP-Med factories process shrimp waste in the medical, pharmaceutical, and cosmetics industries. Finally, the SWPP-PT factories are incorporated into the MESSC network to process shrimp waste materials and provide the paper and textile industries with the required bioactive compounds. The main assumptions of this study in formulating the MESSC problem are explained as follows.

The MESSC network is designed for one type of shrimp [56]; however, several types of shrimp are available in real-world markets, such as Penaeus Monodon (known as Asian tiger shrimp), Litopenaeus Vannamei (known as Pacific white shrimp), Macrobrachium Rosenbergii (known as Giant freshwater prawn), etc. [80]. In this study, there is no uncertainty in the proposed mathematical model. The demands of customers and end consumers are assumed to be certain parameters that are required to be met at all levels of the network. The shortage is not allowed in this problem.

The shrimp waste generation rate is assumed to be a certain parameter during the transportation to and from the established distribution centers. Studying the correlation between the rate of shrimp waste and other factors (*e.g.*, the distance between different elements of the supply network, time of the day, and types of vehicles) is beyond the scope of this study. In addition, the generation rates of shrimp waste in retailers and processing factories are known parameters representing the approximate percentage of waste after removing the head, shell, and tail portions of the supplied shrimps. Finally, the locations of all facilities, fisheries, and shrimp farms are known in the proposed MESSC network, except the locations of distribution centers. Wholesalers can establish a limited number of distribution centers in the potential locations.

Table 2 Sets and Indices.

Set	Definition
I	Set of available commercial fisheries;$i \in I$
J	Set of available shrimp farms;$j \in J$
D	Set of nominated locations for distribution centers;$d \in D$
R	Set of retailers;$r \in R$
F	Set of shrimp processing factories;$f \in F$
C	Set of end customers;$c \in C$
P	Set of products produced in processing factories;$p \in P$
G	Set of shrimp waste processing plants involved in the livestock feeds and aquafeeds markets (SWPP-Food);$g \in G$
A	Set of shrimp waste processing plants involved in the compost markets (SWPP-Agri);$a \in A$
M	Set of shrimp waste processing plants involved in the medical, pharmaceutical, and cosmetics industries (SWPP-Med);$m \in M$
H	Set of shrimp waste processing plants involved in the paper and textile industries (SWPP-PT);$h \in H$
W	Set of all shrimp waste processing plants;$w \in W = \{G \cup A \cup M \cup H\}$

3.2. Modeling notation

In this sub-section, various components of the network which will be applied to formulate the mathematical model, are presented in Tables 2 to 4.

3.3. Mathematical model

In this section, the introduced MESSC network is mathematically formulated. The optimization model is elaborately expounded in the following sub-sections.

3.3.1. Objective functions

In the current industrial atmosphere, enterprises are struggling to ingeniously allocate limited financial and non-financial resources to key processes and sectors with the aim of surviving in the current competitive market and maintaining their competitive advantages. One of the vital sectors in industries is the supply chain which significantly influences the production cost. Therefore, companies are determined to establish supply chain practices at the lowest cost and guarantee more profitability and efficacy [81,82]. With this in mind, the leading function is to financially adjust the supply chain network. In the proposed model, the first objective function aims to minimize the total network costs originating from the locating, operating, and transportation activities, as shown in Eq. (1).

Moreover, shrimp waste has undesirable environmental and social impacts such as water pollution, gas emissions, and health threats as previously discussed [12,14]. The second objective function (Eq. (2)) focuses on maximizing the recovery of biomaterials from accumulated shrimp wastes at distribution centers, retailers, and processing factories. The goal of Eq. (2) is to increase the usage of shrimp waste by-products in various industries and decrease their related environmental issues and social disturbance simultaneously. Undoubtedly, the second objective function increases the usage of shrimp waste within the network and consequently results in lower adverse impacts of waste shrimp.

$$Minimize\mathscr{Z}_1 = \left[\sum_{d\in D} X_d EC_d\right] + \left[\sum_{i\in I}\sum_{d\in D} OCD_d QFD_{i,d} + \sum_{j\in J}\sum_{d\in D} OCD_d QAD_{j,d} + (1-\lambda)\sum_{d\in D}\sum_{f\in F} OCF_f QDF_{d,f}\right] + \left[\sum_{i\in I}\sum_{d\in D} TCSDFD_{i,d}QFD_{i,d} + \sum_{j\in J}\sum_{d\in D} TCSDAD_{j,d}QAD_{j,d} + \sum_{d\in D}\sum_{r\in R} TCSDDR_{d,r}QDR_{d,r} + \sum_{d\in D}\sum_{f\in F} TCSDDF_{d,f}QDF_{d,f} + \sum_{f\in F}\sum_{r\in R}\sum_{p\in P} TCSDFR_{f,r}QFR_{f,r,p} + \sum_{d\in D}\sum_{w\in W} TCWDDW_{d,w}QDP_{d,w} + \sum_{f\in F}\sum_{w\in W} TCWDFW_{f,w}QFP_{f,w} + \sum_{r\in R}\sum_{w\in W} TCWDRW_{r,w}QRP_{r,w}\right] \quad (1)$$

$$Maximize\mathscr{Z}_2 = \sum_{w\in W} QB_w \quad (2)$$

3.3.2. Constraints

Here, the constrains of the optimization model are elaborated:

$$\sum_{d\in D} X_d \le MD \quad (3)$$

$$QD_d = \sum_{i\in I} QFD_{i,d} + \sum_{j\in J} QAD_{j,d} \forall d \in D \quad (4)$$

$$\sum_{d\in D} QFD_{i,d} \le CapF_i \forall i \in I \quad (5)$$

$$\sum_{d\in D} QAD_{j,d} \le CapA_j \forall j \in J \quad (6)$$

$$QD_d \le CapD_d X_d \forall d \in D \quad (7)$$

$$\sum_{r\in R} QDR_{d,r} + \sum_{f\in F} QDF_{d,f} \le QD_d \forall d \in D \quad (8)$$

$$(1-\lambda)\sum_{d\in D} QDF_{d,f} \le CapP_f \forall f \in F \quad (9)$$

$$(1-\lambda)\sum_{d\in D} QDR_{d,r} \le CapR_r \forall r \in R \quad (10)$$

$$QF_{f,p} = \xi_p(1-\lambda)\sum_{d\in D} QDF_{d,f} \forall f \in F, p \in P \quad (11)$$

$$QSWP_f = \left(1 - \sum_{p\in P}\xi_p\right)(1-\lambda)\sum_{d\in D} QDF_{d,f} \forall f \in F \quad (12)$$

Table 3 Parameters.

Parameter	Definition
$DFD_{i,d}$	Driving distance between commercial fishery i and distribution center d (km)
$DAD_{j,d}$	Driving distance between shrimp farm j and distribution center d (km)
$DDR_{d,r}$	Driving distance between distribution center d and retailer r (km)
$DDF_{d,f}$	Driving distance between distribution center d and processing factory f (km)
$DFR_{f,r}$	Driving distance between processing factory f and retailer r (km)
$DDW_{d,w}$	Driving distance between distribution center d and shrimp waste processing plant w (km)
$DFW_{f,w}$	Driving distance between processing factory f and shrimp waste processing plant w (km)
$DRW_{r,w}$	Driving distance between retailer r and shrimp waste processing plant w (km)
TCS	Transportation cost of one unit shrimp between different facilities in the network ($USD/kg \times km$)
TCW	Transportation cost of one unit waste between different facilities ($USD/kg \times km$)
EC_d	Establishment cost of potential distribution center d
OCD_d	Operational cost of potential distribution center d for holding and handling fresh shrimps (USD/kg)
OCF_f	Operational cost of processing factory f for holding and processing fresh shrimps (USD/kg)
$CapF_i$	Capacity of commercial fishery i to provide shrimp to distribution centers (kg)
$CapA_j$	Capacity of shrimp farm j to provide shrimp to distribution centers (kg)
$CapD_d$	Capacity of distribution center d to store and ship shrimps to retailers and processing factories (kg)
$CapR_r$	Capacity of retailer r to receive fresh shrimps from distribution centers (kg)
$CapP_f$	Capacity of factory f to store and process fresh shrimps (kg)
$CapWP_w$	Capacity of shrimp waste processing plant w for processing shrimp waste (kg)
DF_c	Imposed demand by customer c for fresh shrimp (kg)
$DR_{c,p}$	Imposed demand by customer c for shrimp product p from retailers (kg)
$DP_{c,p}$	Imposed demand by customer c for shrimp product p directly from processing factories (kg)
λ	Proportion of shrimp waste generated during the transportation
ψ	Proportion of shrimp waste generated at retailers (for fresh products)
ξ_p	Production rate of product p at processing factories
$\mathscr{RB}_w$	The recovery rate of the biomaterials from accumulated waste at processing plant w
MD	The highest number of distribution centers that can be established by wholesalers

$$QSWD_d = \lambda\left(\sum_{r\in R} QDR_{d,r} + \sum_{f\in F} QDF_{d,f}\right)\forall d \in D \quad (13)$$

$$QSWR_r = \psi(1-\lambda)\sum_{d\in D} QDR_{d,r} \forall r \in R \quad (14)$$

$$\sum_{c\in C} DF_c \le (1-\psi)(1-\lambda)\sum_{d\in D}\sum_{r\in R} QDR_{d,r} \quad (15)$$

Table 4 Decision Variables.

Variable	Definition
X_d	If distribution center d is established at its potential location 1; Otherwise 0.
QD_d	Quantity of fresh shrimps transported from suppliers and delivered to distribution center d (kg)
$QFD_{i,d}$	Quantity of fresh shrimps transported from commercial fishery i to distribution center d (kg)
$QAD_{j,d}$	Quantity of fresh shrimps transported from shrimp farm j to distribution center d (kg)
$QDR_{d,r}$	Quantity of fresh shrimps transported from distribution center d to retailer r (kg)
$QDF_{d,f}$	Quantity of fresh shrimps transported from distribution center d to processing factory f (kg)
$QF_{f,p}$	Quantity of shrimp product p produced at processing factory f (kg)
$QFR_{f,r,p}$	Quantity of shrimp product p transported from processing factory f to retailer r (kg)
$QSWD_d$	Quantity of shrimp waste generated during transportation from distribution center d (kg)
$QSWR_r$	Quantity of shrimp waste generated at retail r (kg)
$QSWP_f$	Quantity of shrimp waste generated at processing factory f (kg)
$QDP_{d,w}$	Quantity of shrimp waste transported from distribution center d to shrimp waste processing plant w (kg)
$QRP_{r,w}$	Quantity of shrimp waste transported from retailer r to shrimp waste processing plant w (kg)
$QFP_{f,w}$	Quantity of shrimp waste transported from processing factory f to shrimp waste processing plant w (kg)
QB_w	Quantity of biomaterials recovered from accumulated waste at waste processing plant w (kg)

$$\sum_{c\in C} DR_{c,p} \le \sum_{f\in F}\sum_{r\in R} QFR_{f,r,p} \forall p\in P \tag{16}$$

$$\sum_{c\in C} DP_{c,p} \le \sum_{f\in F} QF_{f,p} - \sum_{f\in F}\sum_{r\in R} QFR_{f,r,p} \forall p\in P \tag{17}$$

$$\sum_{r\in R} QFR_{f,r,p} \le QF_{f,p} \forall f\in F, p\in P \tag{18}$$

$$\sum_{w\in W} QDP_{d,w} \le QSWD_d \forall d\in D \tag{19}$$

$$\sum_{w\in W} QRP_{r,w} \le QSWR_r \forall r\in R \tag{20}$$

$$\sum_{w\in W} QFP_{f,w} \le QSWP_f \forall f\in F \tag{21}$$

$$\sum_{d\in D} QDP_{d,w} + \sum_{r\in R} QRP_{r,w} + \sum_{f\in F} QFP_{f,w} \le CapWP_w w\in W \tag{22}$$

$$QB_w = \mathscr{RB}_w\left(\sum_{d\in D} QDP_{d,w} + \sum_{r\in R} QRP_{r,w} + \sum_{f\in F} QFP_{f,w}\right) w\in W \tag{23}$$

$$X_d \in \{0,1\} \forall d\in D \tag{24}$$

$$QD_d, QFD_{i,d}, QAD_{j,d}, QDR_{d,r}, QDF_{d,f}, QF_{f,p}, QFR_{f,r,p}, QSWD_d, QSWR_r, QSWP_f, QDP_{d,w}, QRP_{r,w}, QFP_{f,w}, QB_w \ge 0 \forall i\in I, j\in J, d\in D, r\in R, f\in F, c\in C, p\in P, w\in W \tag{25}$$

Eq. (3) denotes that wholesalers can establish a limited number of distribution centers during the planning horizon. Eq. (4) determines the total quantity of fresh shrimp transported from commercial fisheries and shrimp farms and then stored at a potential distribution center. The capacity constraints for the amount of fresh shrimps that can be supplied to distribution centers by a commercial fishery and a shrimp farm are respectively indicated in Eqs. (5) and (6). Eq. (7) displays the capacity of a potential distribution center in receiving and storing fresh shrimps from suppliers and simultaneously ensures that there will be no flow of shrimps to a potential center if it is not established. Eq. (8) guarantees that the total amount of fresh shrimps shipped from an opened distribution center to the retailers and processing factories cannot exceed the amount of shrimps stored at that center. Correspondingly, Eq. (9) ensures that the total amount of fresh shrimp shipped from all established distribution centers and delivered to a processing factory cannot exceed the storing and processing capacity of that factory. A similar constraint applies to the retailers in Eq. (10). Based on the average production rate of shrimp products, which is assumed to be known in this study, and the total amount of fresh shrimp delivered to a processing factory, the quantity of each manufactured product in each processing factory is computed in Eq. (11). Accordingly, the quantity of shrimp waste generated during the production process is calculated by Eq. (12). Likewise, Eqs. (13) and (14) respectively compute the total quantity of shrimp waste generated during the transportation from distribution centers and the storage of shrimp at retailers. Considering the amount of shrimp waste generated during the transportation, delivery, and storage operations, Eq. (15) ensures an adequate supply of fresh shrimp to satisfy the expected demands of customers for fresh products at retail stores. Likewise, Eqs. (16) and (17) satisfy the demand of customers for processed shrimp products that should be supplied by retail stores and processing factories, respectively. Moreover, Eq. (18) expresses that the total amount of a shrimp product shipped from a processing factory to all retailers cannot surpass the total production of that product at the corresponding factory. Eqs. (19)-(21) guarantee that the quantity of waste transferred from a distribution center, retailer, and processing factory to all shrimp waste processing plants must be equal to or less than the total amount of waste generated at the corresponding center. The capacity constraint for a waste processing plant in storing and processing shrimp waste is indicated in Eq. (22). The total quantity of biomaterials recovered from accumulated waste at a waste processing plant is computed by Eq. (23). Finally, the binary and non-negativity constraints for the decision variables are respectively presented in Eqs. (24) and (25).

4. Solution approach

The logistics, SCND, and distribution network problems are mainly solved using exact, heuristics, and metaheuristics techniques. The recent studies in these areas certify that the CLSCNs are marked as NP-hard architecture [83,84]. Accordingly, the

MESSC network can be distinguished as an NP-hard problem. The metaheuristic algorithms are well-structured approaches to overcome the NP-harness of these complex problems [85,86].

Therefore, four distinguished metaheuristic optimizers are framed to tackle the computational complexity of the proposed optimization model in this study, including the Multi-Objective Tabu Search (MOTS), Multi-Objective Grey Wolf Optimizer (MOGWO), Multi-Objective Keshtel Algorithm (MOKA), and Multi-Objective Golden Eagle Optimizer (MOGEO). The performance of metaheuristic algorithms is assessed using standard measures. In addition, the means plot and the least significant difference (LSD) intervals are executed to compare the superiority of optimizers against each other.

4.1. Priority-based encoding strategy

Finding feasible solutions consistent with the formulation and constraints of complex mathematical models are highly essential. A series of techniques are available to help researchers in finding the initial solutions, such as the matrix representation, spanning tree, Prüfer numbers, and Priority-based encoding (PE) [87]. However, PE is one of the most powerful techniques in forming feasible solutions for SCND problems [88] that covers the drawbacks of other methods, such as failing in feasibility criteria [89]. PE creates a uniformly distributed array between 0 and 1 with respect to the scale of the problem. The arrays are sorted ascendingly or descending, and then an integer number is labeled based on the order of each cell. In the following, an instance is organized to enlighten the process.

The proposed MESSC network comprises commercial fisheries (I), shrimp farms (J), distribution centers (D), retailers (R), shrimp processing factories (F), end customers (C), SWPP-Food (G), SWPP-Agri (A), SWPP-Med (M), and SWPP-PT (H). In this example, the number of each component is shown in $\{I, J, D, R, F, C, G, A, M, H\} = \{3, 3, 2, 2, 3, 2, 2, 2, 1, 2\}$ set. PE technique implies that the array must have $I + J + 3D + 4R + 3F + 2C + G + A + M + H = 40$ cells. Fig. 3 illustrates the analyzed appearance of the array. If we observe the whole network as providers and receivers, the array can be shown in five sections. In the first section, Fig. 3 (a), the product flow is considered between commercial fisheries, shrimp farms, and distribution centers. The process starts from the left cell of the sender and receiver, and the product flow is continued until the whole capacity or demand of the receiver is satisfied. This process chain is stretched to the final components so that the capacities and demands of all components are met.

4.2. Multi-objective Tabu search

Single-solution optimizers are attributed as a particular type of metaheuristics concentrating on only one single feasible solution in the optimization process. Tabu Search (TS) possesses one of the solid exploration and exploitation phases in addressing optimization problems among single-solution optimizers. This optimizer is firstly introduced by Glover (1989) to avoid cycling using a tabu list, which enables the algorithm to explore other possible alternatives [90]. The tabu status is constrained in terms of time, so the elements of tabu list will be available after a default time. The MOTS is extended to solve multi-objective problems, and the literature reveals successful implementation of this algorithm (*e.g.,* Hamid et al. (2020) [91]). Algorithm A.1 shows the pseudo-code of MOTS in Appendix A.

4.3. Multi-objective grey Wolf optimizer

This novel and recently developed optimizer is one of the most intelligent population-based algorithms which mirrors the

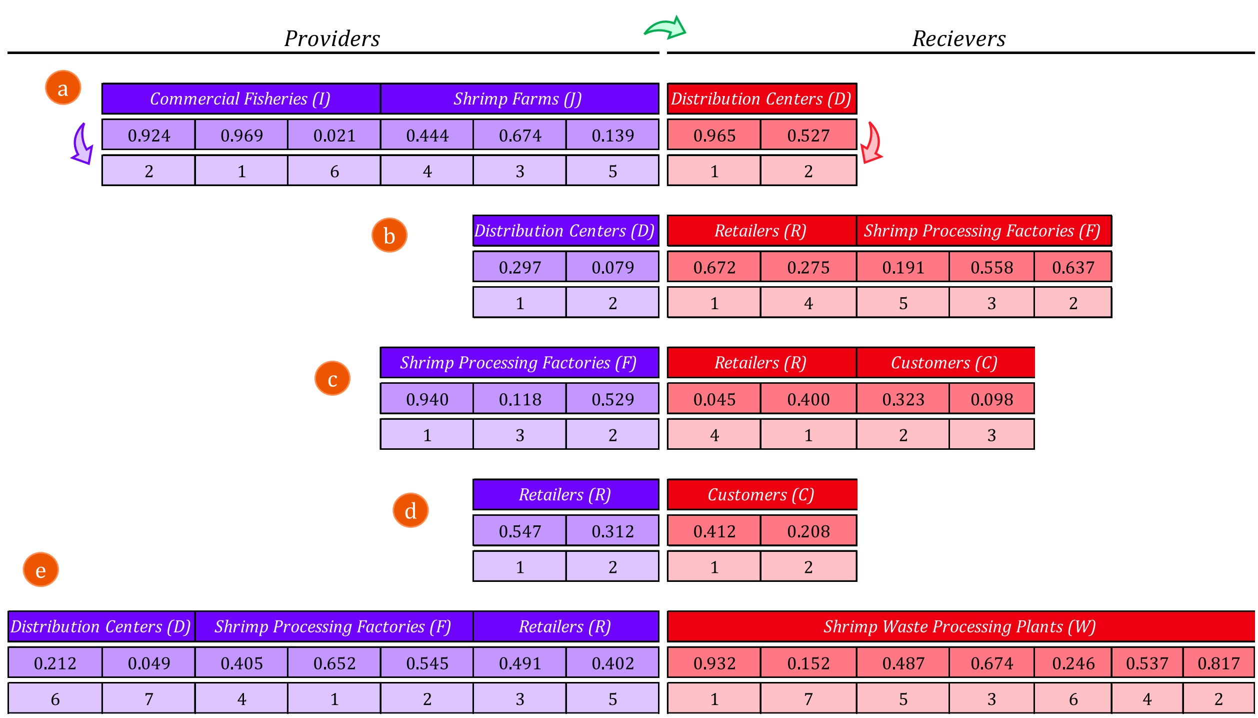


Fig. 3 The representation of chromosomes for the proposed model.

hunting behavior of grey wolfs in a hierarchical arrangement. The three top-ranked wolfs (*i.e.*, α, β, and δ) are the leaders of grey wolf packs (ω) for attacking the prey. The Grey Wolf Optimizer (GWO) was primarily conceptualized and implemented by Mirjalili *et al.* (2014) [92], and the multi-objective extension of GWO was designed by Mirjalili *et al.* in 2016 [93]. Algorithm A.2 displays the pseudo-code of MOGWO in Appendix A.

4.4. Multi-objective Keshtel algorithm

Keshtel Algorithm (KA) is a swarm intelligent and population-based optimizer developed by Hajiaghaei-Keshteli and Aminnayeri (2013) [94], and the MOKA is established for addressing multi-objective optimization problems. KA imitates the behavior of Keshtels (a type of bird) for finding food in the pond. The population of Keshtels is partitioned into three classes: lucky Keshtels, unlucky Keshtels, and the rest of Keshtels. In this algorithm, the swirling, movement, and replacement operators are performed to secure robust diversification and intensification phases. Interested readers are encouraged to refer to Hajiaghaei-Keshteli and Aminnayeri (2014) [95]. Algorithm A.3 demonstrates the pseudo-code of MOKA in Appendix A.

4.5. Multi-objective golden eagle optimizer

The Golden Eagle Optimizer (GEO) is labeled as a population-based metaheuristic that was firstly introduced by Mohammadi-Balani *et al.* in 2021 [96]. Authors set the cruise and predation mechanism for each iteration of the local and global search. The GEO was extended for multi-objective problems by applying crowding distance and non-dominated sorting features. Please refer to [96] for detailed information on the background and capabilities of this algorithm. Algorithm A.4 presents the pseudo-code of MOGEO in Appendix A.

5. Practical analysis

In this section, a test suite in three scales is framed to investigate the functionality and applicability of the proposed model. The designed test suite is precisely chosen to be a solid representation of the network in local, provincial, and regional circumstances. As stated in Table 5, each of the small, medium, and large-scale suites comprise five tests with different dimensions. These test examples examine the ability of metaheuristic optimizers in dealing with the high execution time of the algorithm.

The crucial elements of the mathematical model are its parameters, which need to be defined appropriately to prevent the infeasibility of the model and enable the monitoring and evaluation of performance of algorithms in a similar setting. The required data for the proposed experimental trials is evolved from [77]. Detailed information is available in Table 6.

5.1. Assessment measures

Due to the structure of the multi-objective problems, particular assessment measures are required compared to the single-objective ones. The result of a multi-objective optimizer is obtained as a set of non-dominated or Pareto optimal solutions which needs quantifiable measures for comparison purposes. Among the several measures that have been provided in the literature, five well-structured ones are selected and applied in this study, including the Spread of non-dominated solutions (SNS), Mean ideal distance (MID), Maximum Spread (MS), Hypervolume (HV), and CPU Time (CT). For detailed information on these measures, please refer to [97,98].

5.2. Parameters tuning

The parameters of the metaheuristic algorithms have a fundamental influence on the quality of optimizers and searching the solution space. The parameters need to be tuned to the right level to avert time-consuming and fruitless executions. Nonetheless, the parameters of optimizers have various levels that affect the final outputs [99]. Several tuning approaches have been used in the literature, among which the design of an experiment (DOE) demonstrated a solid performance. Taguchi is one of the most efficient and powerful DOE techniques. In the Taguchi setting, parameters are defined as the factors of the experiment [100]. The most suitable level for a parameter is the one that results in less noise of effect. Moreover, Taguchi takes a response value to accomplish the experiment based on it. In the current study, the inverted

Table 5 Dimensions of the experimental trials.

Indices Scales		*I*	*J*	*D*	*R*	*F*	*C*	*G*	*A*	*M*	*H*	*P*	*T*
Small	DET_1	2	2	3	2	1	1	1	1	1	1	3	3
	DET_2	3	3	4	3	2	3	2	2	2	2	3	3
	DET_3	4	5	6	4	3	3	3	3	3	3	4	3
	DET_4	7	6	8	4	3	5	3	3	4	4	4	6
	DET_5	7	6	8	6	4	5	3	3	4	4	5	6
Medium	DET_6	10	9	12	9	6	7	4	4	6	6	7	6
	DET_7	15	13	18	13	9	10	6	6	9	9	7	6
	DET_8	22	19	27	14	9	11	6	6	9	9	9	9
	DET_9	33	28	40	21	13	16	9	9	13	13	9	9
	DET_{10}	49	42	60	31	19	24	13	13	19	19	9	9
Large	DET_{11}	73	63	90	46	28	36	14	14	20	20	10	12
	DET_{12}	80	69	99	50	30	39	15	15	22	22	10	12
	DET_{13}	88	75	108	55	33	42	16	16	24	24	15	12
	DET_{14}	96	82	118	60	36	46	17	17	26	26	20	24
	DET_{15}	105	90	129	66	39	50	18	18	28	28	20	24

Table 6 Defined range of parameters for the experimental trials.

Parameters	Values	Unit	Parameters	Values	Unit
$DFD_{i,d}$	U ~ (20, 150)	km	$CapF_i$	U ~ (4, 6)	$10^3 \times kg$
$DAD_{j,d}$	U ~ (15, 200)	km	$CapA_j$	U ~ (1, 2)	$10^3 \times kg$
$DDR_{d,r}$	U ~ (40, 120)	km	$CapD_d$	U ~ (7, 9)	$10^3 \times kg$
$DDF_{d,f}$	U ~ (20, 100)	km	$CapR_r$	U ~ (2, 4)	$10^3 \times kg$
$DFR_{f,r}$	U ~ (30, 250)	km	$CapP_f$	U ~ (1, 3)	$10^3 \times kg$
$DDW_{d,w}$	U ~ (20, 180)	km	$CapWP_w$	U ~ (3, 5)	$10^3 \times kg$
$DFW_{f,w}$	U ~ (20, 210)	km	DF_c	U ~ (1, 2)	$10^2 \times kg$
$DRW_{r,w}$	U ~ (25, 90)	km	$DR_{c,p}$	U ~ (2, 3)	$10^2 \times kg$
TCS	U ~ (2, 3)	$USD/kg \times km$	$DP_{c,p}$	U ~ (1, 2)	$10^2 \times kg$
TCW	U ~ (1, 2)	$USD/kg \times km$	λ	U ~ (1, 3)	$10^{-4} \times kg/km$
EC_d	U ~ (200, 500)	$MillionUSD$	ψ	U ~ (4, 5)	$10^{-3} \times kg$
OCD_d	U ~ (4, 7)	USD/kg	ξ_p	U ~ (7, 9)	$10^{-3} \times kg$
OCF_f	U ~ (3, 6)	USD/kg	$\mathscr{RB}_w$	U ~ (20, 40)	$Percent$
MD	10^{10}				

generational distance (IGD) is introduced as the response value in the experiments. The experiments are based on the "smallest is better" framework. For more information on IGD, please refer to [96]. Table 7 expresses the results of Taguchi method and the optimal level of each parameter for the proposed metaheuristic optimizers.

6. Computational outputs

This section demonstrates the results of the metaheuristic optimizers (*i.e.,* MOTS, MOGWO, MOKA, and MOGEO) applied for the proposed MESSC model. As previously stated, three classes of experimental tests and five assessment measures are specified to examine the performance of the algorithms. It is noteworthy to mention that the value of measures differs greatly in each experimental test. Thus, the comparison of results requires a normalization indicator. In this paper, the Relative Deviation Index (RDI) is used to convert the results of measures comparably, as shown in Eq. (26).

$$RDI = \frac{\left|R^i_{Meta} - R^i_{Best}\right|}{R^i_{Max} - R^i_{Min}} \tag{26}$$

In Eq. (26), R^i_{Meta} denotes the value of the evaluation measure obtained in the *i-th* test of the metaheuristic optimizer. R^i_{Best}, R^i_{Max}, and R^i_{Min} represents the best, maximum, and minimum of the evaluation measure in the *i-th* test among all optimizers.

At this point, the means plot and the LSD intervals are represented in four specific classes (*i.e.,* small-scale, medium-scale, large-scale, and overall form) to examine the performance of metaheuristic optimizers. The results of the RDI indicator and LSD plots are reported in Appendix B, Tables B.1–B.5. Generally, it can be concluded that all the applied metaheuristic optimizers are capable of solving the proposed model.

In terms of SNS measure, MOGWO in small-scale problems and MOGEO in the remaining problems have superior performance. In an overall view, MOGEO is located at the top of the optimizers list. Similarly, MOGWO and MOGEO compete closely with each other with respect to MID measure. The perfor-

Table 7 Parameters of the metaheuristic algorithms.

Algorithm	Parameter	Level					Optimal Level
		L_1	L_2	L_3	L_4	L_5	
MOTS	*Maximum Iteration*	50	100	150	175	200	150
	Tabu Size	5	7	10	12	15	7
	Neighbors Number	15 %	20 %	30 %	40 %	50 %	40 %
MOGWO	*Maximum Iteration*	50	100	150	175	200	175
	Initial Population	100	150	200	250	300	100
	Change Position Rate	0.2	0.3	0.35	0.4	0.5	0.5
	*Control Parameter**	$C = [2 - 0]$					
	*Number of Leaders**	$No_{Leaders} = 3$					
MOKA	*Maximum Iteration*	50	100	150	175	200	100
	Initial Population	100	150	200	250	300	150
	S_{max}	5	6	7	8	9	6
	N_1	0.05	0.07	0.09	0.12	0.15	0.12
	N_2	0.20	0.25	0.30	0.33	0.35	0.30
MOGEO	*Maximum Iteration*	50	100	150	175	200	150
	Initial Population	100	150	200	250	300	100
	*Propensity to attack**	$p^0_a = 0.5; p^T_a = 2$					
	*Propensity to cruise**	$p^0_c = 1; p^T_c = 0.5$					

* The parameters with default values.

mance of the MOTS, MOGWO, and MOGEO algorithms in small-scale problems are almost similar. However, MOGEO outperforms other optimizers in medium- and large-scale problems. Despite the tight competition between MOGWO and MOGEO in an overall frame, MOGWO has a dominant demonstration. Considering the MS measure, MOGEO is labeled as the unrivaled metaheuristic optimizer in all groups of experiments. To argue on the performance of optimizers in terms of HV, MOGWO outpaces in all categories except the medium-scale problems in which MOGEO has better performance. Finally, the MOTS algorithm is attributed as the metaheuristic optimizer with the lowest computation time.

6.1. Sensitivity analysis

Sensitivity analysis is exploited to observe the behavior of the mathematical model based on changes in the most effective parameters. In this section, the operational costs, capacities, and demands within the network are indicated as the influential parameters of the proposed model. The nominated problem for the sensitivity analysis is DET_8. Multi-objective problems provide a set of Pareto solutions that can be difficult to use for sensitivity analysis. For this reason, we adopt the weighted sum method with a weight vector $(0.5, 0.5)$ to transform the proposed multi-objective structure into a single-objective one. Calculating the test problem DET_8 demonstrates that the objective function values are $(Z_1, Z_2) = (2.415 \times 10^6 USD, 47165.2kg)$. This case is the neutral status for the sensitivity analysis, which is shown as 0 %. The value of parameters is altered based on the default values reported in Table 6. The results of the sensitivity analyses are sketched in Figs. 4 – 6.

In the first stage, key cost parameters are adjusted between (– 50 %, 50 %) of default values. The parameters are as follows: transportation cost of shrimp products (TCS), transportation cost of shrimp wastes (TCW), establishment cost of distribution centers (EC), operational cost of distribution centers (OCD), and operational cost of processing factories (OCF). The result shows that the total cost of the network faces a sharp rise while the costs are increased. On the contrary, decreasing the cost parameters results in the reduction of total cost. On the other hand, there is a reverse relationship between the waste usage amount and the cost parameters. However, the usage of shrimp waste in the network slightly reacts to the variations in the costs.

In the next step, key capacity parameters are changed to record the shifts in the objective function values. The capacity parameters of the problem comprise the capacity of commercial fisheries ($CapF$), capacity of shrimp farms ($CapA$), capacity of distribution centers ($CapD$), capacity of retailers ($CapR$), capacity of factories ($CapP$), and the capacity of shrimp waste processing plants ($CapWP$). The sensitivity analysis results indicate that the higher network capacities can increase both the total cost and the usage of shrimp waste in the network. In fact, the transportation of shrimp products increases when the network finds that it can transfer a higher quantity of products. As a result, the higher amount of shrimp products leads to more shrimp waste in the network and undoubtedly more transportation costs, operational costs, and waste usage.

Finally, the sensitivity analysis is performed on the demand parameters, including the customer demands for fresh shrimp (DF), customer demands for shrimp products from retailers

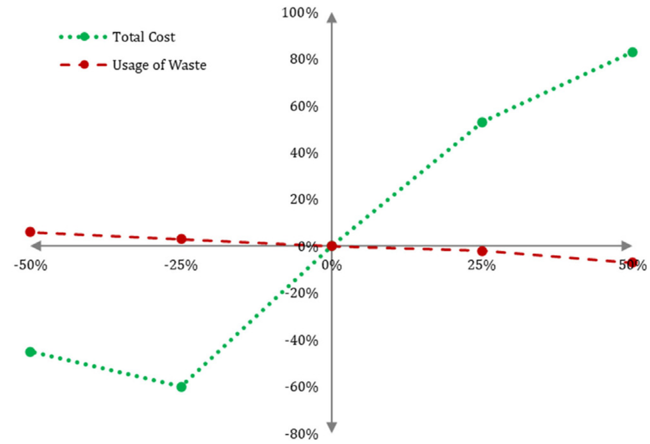


Fig. 4 Sensitivity analysis on the key cost parameters.

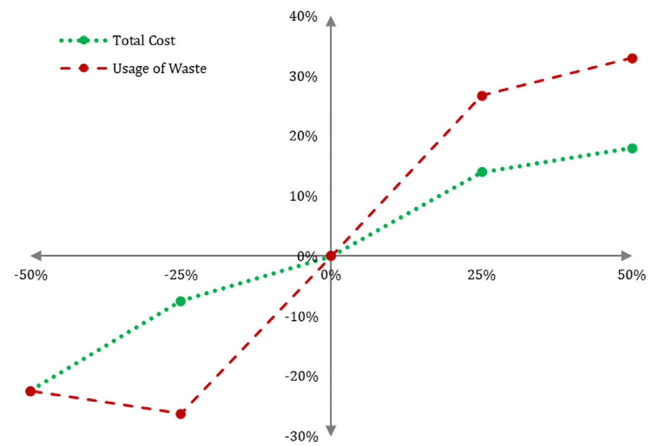


Fig. 5 Sensitivity analysis on the key capacity parameters.

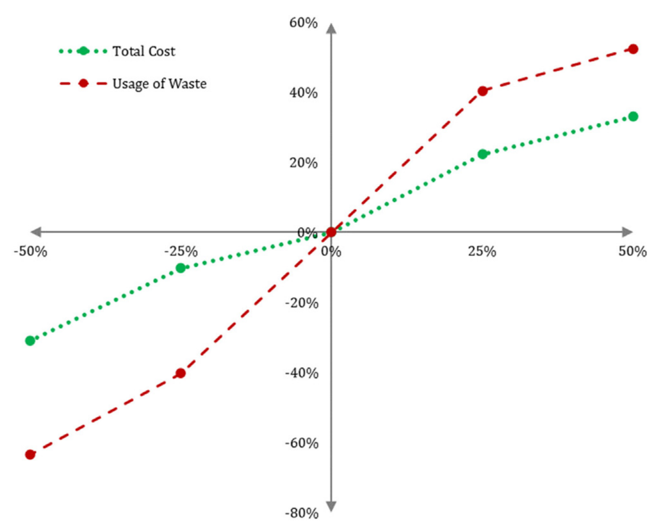


Fig. 6 Sensitivity analysis on the demand parameters.

(DR), and customer demands for shrimp products from processing factories (DP). It can be concluded that the variations in the demand are also positively associated with the values of objective functions. Increasing the amount of demand from

−50 % to 50 % causes the growth of the total cost and usage of shrimp waste within the network. As a matter of fact, meeting the demand of customers requires the transportation and operational activities throughout the network. This is accompanied by more shrimp products, waste usage, and the total cost in the network.

7. Managerial insights

In a nutshell, the managerial insights provide administrators with the achievements of a study to have a better understanding of the direct and indirect impacts of their industries while improving the profitability of their businesses. In this section, based on the research output obtained from the proposed sustainable optimization model, some useful insights are discussed for the decision-makers who have executive management responsibilities in the seafood supply chain sector.

In this work, it is attempted to study the seafood supply chain area in a distinctive way than the existing literature and distinguish the proposed model by exploiting essential elements of the actual seafood supply chain network. For this purpose, the main players in the seafood products supply chain (*i.e.,* commercial fisheries, shrimp farms, distribution centers, markets, processing factories, and waste processing plants) are considered to help the managers of industries and businesses in this scope with the synchronized reduction of expenses as well as the mitigation of social and environmental impacts.

The managers, policymakers, or stakeholders of shrimp businesses can deploy the proposed model to ideally design a facility location problem while responding effectively and equitably to the demands of the shrimp products and the by-products produced from the shrimp waste. Furthermore, they can benefit from the production planning and distribution capabilities of the model to not only monitor the processes within the network, but also balance the cost of various activities such as locating, operating, and transportation.

Additionally, waste products are of common concern of all sustainable industries, especially those that receive perishable items as their raw material. In the case of seafood products, the industries are aware of the adverse consequences of shrimp waste, such as negative impacts on the health situation of societies or environmental impacts on the marine regions. As a result, they are actively seeking a solution to overcome harmful influences of shrimp waste. Hereby, the proposed multi-objective multi-product model is equipped with environmental and social attention. In this regard, the managers can implement the model to increase the overall level of waste usage in the network. This assists shrimp-related industries in reducing the shrimp waste load by maximizing waste usage and converting waste materials into valuable products that can be used in the next stages of the network. Thus, the proposed model can provide supply chain managers with opportunities to reinforce their competitive advantages and move towards more profitability while satisfying the demands of shrimp products and by-products from their wastes.

8. Conclusions

Seafood products are an excellent source of essential nutrients for human health. Recently, various drivers have caused malfunctions and deficiencies within the seafood supply chain network, such as sustainability regulations, pandemics, and economic factors. Due to the impact of seafood products on the food security, health, and well-being of people, this paper aimed to enhance the SFSCN performance by adding new features from prior works in agri-food and seafood supply chain networks. To this end, a multi-echelon supply chain was developed for a fresh seafood network considering sustainability factors. To study the applicability and compatibility of the optimization model in real-world settings, the proposed network is customized for shrimp products. The proposed mathematical model aimed to form the sustainability context by optimizing the total network cost, as economic factor, and the waste recovering activities as the social and environmental aspects.

The proposed multi-echelon shrimp supply chain network is an *NP*-hard problem. To conquer the complexity of the mathematical model, a set of metaheuristic-based methodologies (*i.e.,* MOTS, MOGWO, MOKA, and MOGEO) were applied in solving different dimensions of the problem. To analyze the functionality and capability of the solution approaches, 15 test problems in three different scales (*i.e.,* small, medium, and large) are prepared. The Taguchi technique is applied to determine the optimal parameters for each metaheuristic optimizer. Subsequently, the metaheuristic optimizers were evaluated utilizing five evaluation measures: SNS, MID, MS, HV, and CT. Then, the obtained value of each measure is normalized using the RDI indicator to facilitate the statistical analysis process. In addition, to compare the performance of algorithms, the mean plot and the LSD intervals were provided for all measures in different problem scales and the overall form. From the obtained results and based on the evaluation measures, it can be inferred that the MOGWO and MOGEO algorithms can outperform MOKA and MOTS methods in solving all test problems. However, the MOTS algorithm was the most efficient metaheuristic optimizer in terms of running time in the designed framework.

This research experienced a number of barriers from the theoretical and technical views, which include (I) limitation in having access to actual data of the seafood business due to confidentiality concerns which prevents the adoption of data from past studies in a related field, (II) difficulties in finding the right value for production and recovery rates in the forward and reverse flows of products, (III) difficulties in the determination of appropriate problem scales for the experimental trials, (IV) lack of a benchmark study in the SFSCN literature, as well as the lack of access to the real case scenarios.

There are multiple future directions for this study from theoretical and methodological viewpoints. For those industries that are dealing with stochasticity in their problems, it is suggested to overcome the uncertainty of parameters using two well-known techniques: (1) Stochastic Programming (SP) if decision-makers have access to the historical records of required data and can achieve the probability distribution of parameters; (2) Robust Optimization (RO) in the case of lack of information and historical data. Moreover, it is recommended to formulate the smart supply chain network by applying the Internet of Things (IoT) or blockchain concepts. Finally, employing relaxation or decomposition methods and applying other heuristics or hybrid metaheuristic algorithms might enhance the performance of solution approaches in solving the large-sized optimization problems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Algorithm A.1: Multi-Objective Tabu Search (MOTS).

```
Input(s): parameters, model, fitness functions.
Initialize the parameters.
Form a set of Pareto non-dominated solutions (P_ns).
Create an empty set for optimized Pareto solutions (P_os).
while |P_NS| > | P_OS |
   Select a solution P_O from P_NS.
   Clear the Tabu List.
   Current Iteration = 1.
   while Current Iteration < Max Iteration
      Create a set of feasible neighborhood solution (N_s) for P_o.
      Evaluate fitness function of N_s.
      if Aspiration condition is hold.
         The solution is replaced by the best solution.
      else if
         Select the solution as the best solution which is not
forbidden.
      end if
      Update tabu list, and P_os.
   end while
   Update P_ns.
end while
Output(s): P_os, fitness value of P_os
```

Algorithm A.2: Multi-Objective Grey Wolf Optimizer (MOGWO).

```
Input(s): parameters, model, fitness functions.
Initialize the parameters.
Form population of grey wolves (W).
Calculate fitness function of W.
Perform non-dominated sorting and crowding distance.
Current Iteration = 1.
while Current Iteration < Max Iteration
   for each member of W
      Find the leaders for pack of wolves.
      Follow the leaders.
      Probe the adjacency.
   end for
   Calculate fitness function for the generated population.
   Merge the generated population and old population.
   Perform non-dominated sorting and crowding distance.
   Select W best grey wolves for next iteration.
end while
Output(s): Optimal W, fitness value of Optimal W.
```

Algorithm A.3: Multi-Objective Keshtel Algorithm (MOKA).

```
Inputs: parameters, model, fitness functions.
Initialize the parameters.
Form population of Keshtels (K).
Calculate fitness function of K.
Perform non-dominated sorting and crowding distance.
Create empty set for optimized Keshtel (K_op)
Current Iteration = 1.
while Current Iteration < Max Iteration
   Select N_1 best Keshtels and mark as the lucky Keshtels (LK)
   for LK_i Keshtels in LK
      Obtain the distance between LK_i and K.
      Choose the nearest solution and implement swirling operator
(L_sw).
      Replace LK provided that the better fitness value discovered
by swirling.
   end for
   Select N_2 best Keshtels excluding LK and perform movement.
   Select the remaining Keshtels and replace with new Keshtels.
   Combine N_1, N_2, N_3 and perform non-dominated sorting and
crowding distance.
   Separate K best Keshtels (K_op) and consider form new
iteration.
end while
Outputs: K_op, fitness value of K_op
```

Algorithm A.4: Multi-Objective Golden Eagle Optimizer (MOGEO).

```
Input(s): parameters, model, fitness functions.
Initialize the parameters.
Form population of golden eagles (E).
Calculate fitness function of E.
Current Iteration = 1.
while Current Iteration < Max Iteration
   Update attack and cruise parameters.
   Calculate crowding distance of E.
   for each member of E
      Select a random prey and calculate attack vector →AV.
      if length of →AV is greater than zero
         Calculate cruise and step vectors.
         Update position (UE).
         Calculate fitness function of UE.
         if the UE is non-dominated
            if external archive is not fully loaded.
               Add a new eagle to the archive.
            else if
               Obtain the sparsity distance and find the outgoing
eagle.
               Replace the outgoing eagle with a new one.
            end if
         end if
      end if
   end for
end while
Output(s): Optimal E, fitness value of Optimal E.
```

Appendix B. See Tables B1-B5

Table B1 The results of SNS indicator for metaheuristic algorithms and LSD intervals.

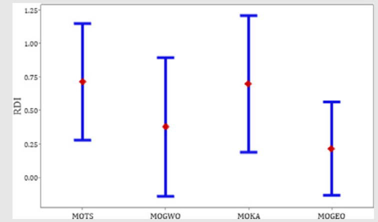
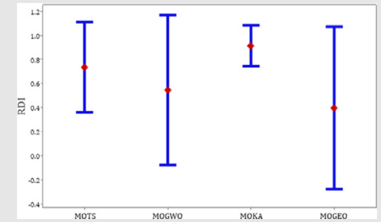
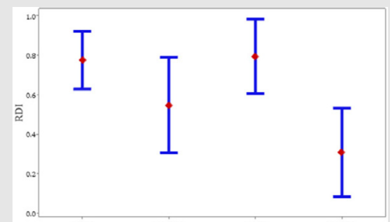
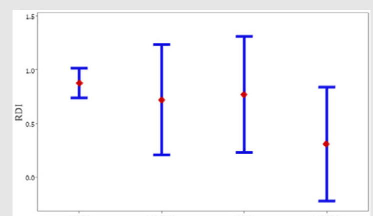
Scale		MOTS	MOGWO	MOKA	MOGEO	Interval Plots (For each scale)	Interval Plot (Full Experiments/Overall Form)
Small	*DET* $_1$	5.01543E + 06	9.55691E + 06	6.07751E + 06	9.43464E + 06		
	DET $_2$	1.34870E + 07	1.69870E + 07	8.89328E + 06	1.23970E + 07		
	DET $_3$	2.28900E + 07	2.17823E + 07	3.14960E + 07	2.69882E + 07		
	DET $_4$	3.31768E + 07	3.89752E + 07	3.57896E + 07	4.21719E + 07		
	DET $_5$	5.11944E + 07	4.61609E + 07	3.74654E + 07	5.57715E + 07		
Medium	*DET* $_6$	6.09741E + 07	5.57468E + 07	5.49570E + 07	6.29483E + 07		
	DET $_7$	6.78723E + 07	6.33665E + 07	5.69540E + 07	9.16366E + 07		
	DET $_8$	8.88200E + 07	7.91927E + 07	9.20100E + 07	1.18922E + 08		
	DET $_9$	9.21288E + 07	1.51937E + 08	9.65884E + 07	9.09565E + 07		
	DET $_{10}$	9.96790E + 07	1.73853E + 08	1.00990E + 08	1.00939E + 08		
Large	*DET* $_{11}$	1.15903E + 08	1.11909E + 08	1.07946E + 08	1.85954E + 08		
	DET $_{12}$	1.29959E + 08	1.15997E + 08	1.92976E + 08	1.28990E + 08		
	DET $_{13}$	1.32886E + 08	1.36899E + 08	1.29933E + 08	2.03954E + 08		
	DET $_{14}$	1.66909E + 08	2.55950E + 08	1.79949E + 08	1.91951E + 08		
	DET $_{15}$	2.17999E + 08	2.13885E + 08	1.87985E + 08	2.94952E + 08		

Table B2 The results of MID indicator for metaheuristic algorithms and LSD intervals.

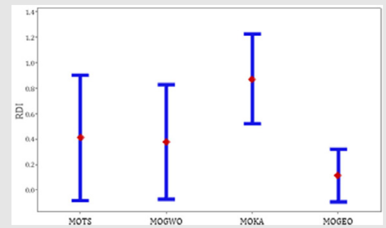
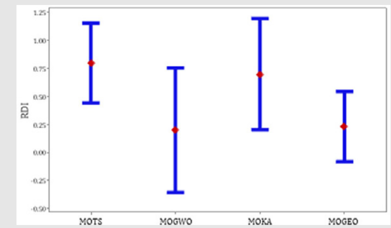
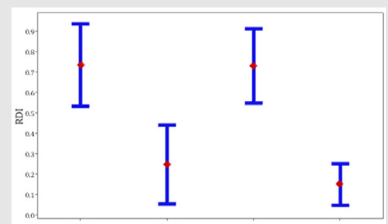
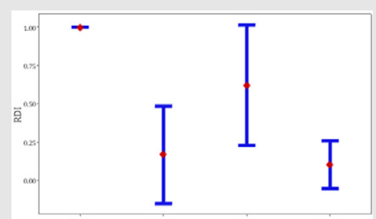
Scale		MOTS	MOGWO	MOKA	MOGEO	Interval Plots (For each scale)	Interval Plot (Full Experiments/Overall Form)
Small	*DET₁*	4.47	4.71	3.48	2.77		
	DET 2	4.15	2.87	5.57	2.67		
	DET 3	4.66	4.01	5.38	3.29		
	DET 4	2.40	3.27	6.29	3.20		
	DET 5	2.24	2.75	4.30	3.00		
Medium	*DET 6*	4.08	2.64	3.81	3.59		
	DET 7	2.77	2.48	2.72	2.52		
	DET8	4.05	4.80	2.91	3.20		
	DET 9	4.75	3.76	6.33	3.76		
	DET 10	5.37	2.75	5.04	3.33		
Large	*DET 11*	5.80	5.64	2.33	2.91		
	DET 12	2.96	2.87	2.07	2.13		
	DET 13	4.96	4.58	4.52	3.91		
	DET 14	4.21	2.59	2.09	1.32		
	DET 15	5.82	3.33	2.73	3.63		

Table B3 The results of MS indicator for metaheuristic algorithms and LSD intervals.

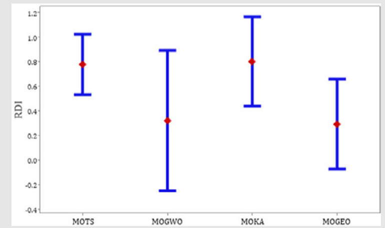
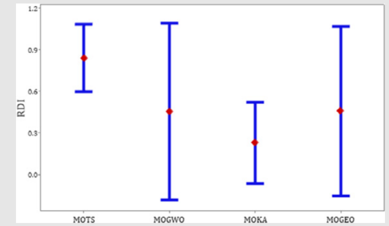
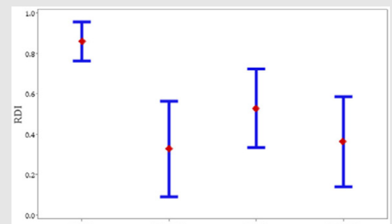
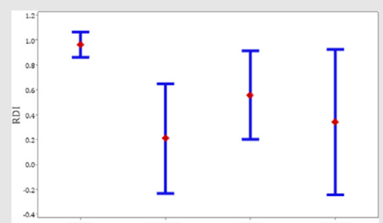
Scale		MOTS	MOGWO	MOKA	MOGEO	Interval Plots (For each scale)	Interval Plot (Full Experiments/Overall Form)
Small	DET_1	7.97746E + 06	1.92813E + 07	1.53899E + 07	1.27877E + 07		
	DET_2	3.61679E + 07	4.04803E + 07	2.75902E + 07	6.01724E + 07		
	DET_3	5.14502E + 07	9.85707E + 07	3.55975E + 07	6.02823E + 07		
	DET_4	7.38689E + 07	1.12954E + 08	7.04788E + 07	1.00914E + 08		
	DET_5	1.79900E + 08	9.76293E + 07	1.50936E + 08	2.57802E + 08		
Medium	DET_6	1.89861E + 08	3.42937E + 08	2.15881E + 08	1.09945E + 08		
	DET_7	3.30804E + 08	2.54876E + 08	4.40828E + 08	4.43711E + 08		
	DET_8	2.92977E + 08	4.64774E + 08	3.98876E + 08	3.02849E + 08		
	DET_9	2.71876E + 08	4.52709E + 08	4.69898E + 08	5.14911E + 08		
	DET_{10}	3.28877E + 08	2.99800E + 08	7.56883E + 08	6.05452E + 08		
Large	DET_{11}	1.24877E + 09	4.10687E + 09	2.77854E + 09	6.08690E + 08		
	DET_{12}	9.89736E + 08	9.51873E + 09	2.88943E + 09	3.68929E + 09		
	DET_{13}	2.29961E + 09	3.66735E + 09	3.87842E + 09	9.99599E + 09		
	DET_{14}	1.64869E + 09	5.83698E + 09	2.94799E + 09	5.75932E + 09		
	DET_{15}	1.90843E + 09	7.73326E + 09	8.30272E + 09	9.33273E + 09		

Table B4 The results of HV indicator for metaheuristic algorithms and LSD intervals.

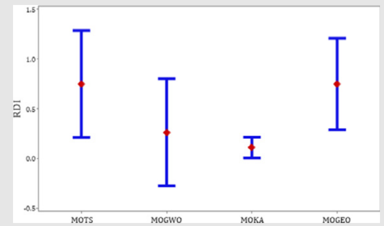
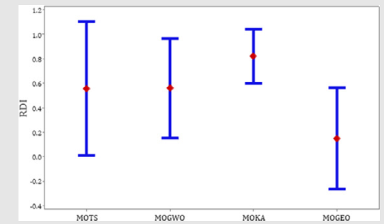
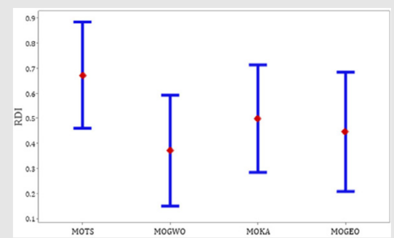
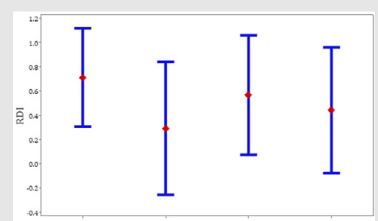
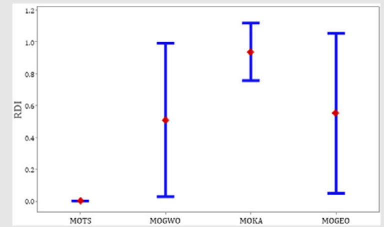
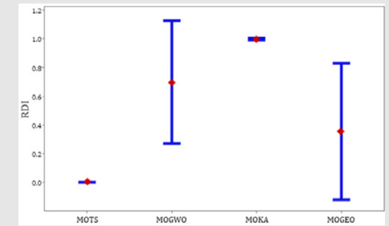
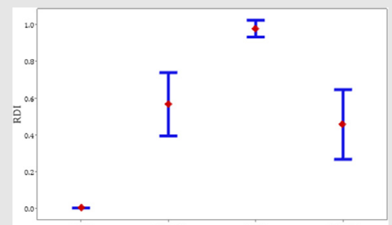
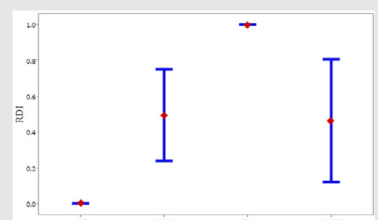
Scale		MOTS	MOGWO	MOKA	MOGEO	Interval Plots (For each scale)	Interval Plot (Full Experiments/Overall Form)
Small	*DET* $_1$	7.90667E + 07	1.56863E + 08	1.88821E + 08	9.09873E + 07		
	DET $_2$	3.80881E + 08	5.80748E + 08	5.69710E + 08	4.22623E + 08		
	DET $_3$	4.40652E + 08	6.70918E + 08	6.45795E + 08	6.48973E + 08		
	DET $_4$	1.78906E + 09	2.09896E + 09	2.03940E + 09	1.67893E + 09		
	DET $_5$	2.86854E + 09	2.22854E + 09	2.72888E + 09	2.26961E + 09		
Medium	*DET* $_6$	3.35704E + 09	3.37782E + 09	2.98945E + 09	3.73913E + 09		
	DET $_7$	3.68995E + 09	5.06719E + 09	4.38619E + 09	7.34854E + 09		
	DET $_8$	3.73992E + 09	5.71455E + 09	5.28689E + 09	8.88305E + 09		
	DET $_9$	8.04974E + 09	5.76813E + 09	7.04637E + 09	8.94225E + 09		
	DET $_{10}$	1.32917E + 10	1.27959E + 10	8.49410E + 09	9.70890E + 09		
Large	*DET* $_{11}$	1.38881E + 10	2.13961E + 10	1.47927E + 10	1.73931E + 10		
	DET $_{12}$	2.68810E + 10	3.19886E + 10	2.25805E + 10	2.61920E + 10		
	DET $_{13}$	2.78897E + 10	3.53850E + 10	3.22865E + 10	3.49884E + 10		
	DET $_{14}$	4.66720E + 10	4.36885E + 10	4.97938E + 10	3.64673E + 10		
	DET $_{15}$	4.91535E + 10	4.53731E + 10	5.31629E + 10	6.27490E + 10		

Table B5 The results of CT indicator for metaheuristic algorithms and LSD intervals.

Scale		MOTS	MOGWO	MOKA	MOGEO	Interval Plots (For each scale)	Interval Plot (Full Experiments/Overall Form)
Small	T_1	17.91	52.21	54.61	40.98		
	T_2	54.00	75.36	191.89	171.36		
	T_3	89.09	119.38	170.57	209.70		
	T_4	207.27	322.87	629.07	285.68		
	T_5	570.08	705.58	716.80	581.77		
Medium	T_6	718.51	755.16	938.95	812.81		
	T_7	719.80	1638.98	1628.77	867.86		
	T_8	1350.86	2139.10	2133.40	2127.16		
	T_9	3063.50	6455.69	7921.42	3909.08		
	T_{10}	3713.43	7458.08	9804.51	3814.72		
Large	T_{11}	4744.52	7702.50	12239.24	8344.80		
	T_{12}	6232.14	7529.28	13193.75	8564.64		
	T_{13}	8690.55	11095.43	13003.28	9207.45		
	T_{14}	10705.77	17249.49	20913.00	15900.00		
	T_{15}	14030.49	18805.92	20942.60	20059.20		

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