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Research Article

Supply Chain Management (SCM) Breakdowns and SCM Strategy Selection during the COVID-19 Pandemic Using the Novel Rough MCDM Model

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Supply chain management (SCM) is deeply affected by the COVID-19 pandemic besides breakdowns occurred in all sectors. Nowadays, managers need techniques for protecting supply chains from serious and costly disruptions, establishing permanent relationships with the customers and partners and preventing breakdowns throughout the process. Each firm needs to determine SCM strategies to be prepared for breakdowns in an intense competitive environment. With COVID-19, the change in business and trade environments has taken a different dimension, and it has revealed a new relationship between the efforts to perpetuate supply chains and strategies for supply chain management and enabled new models. In this study, it is aimed to prioritize the factors that lead to SCM breaks needed in project management and the realization of projects, and to choose the most successful SCM strategy considering COVID-19. For this purpose, rough SWARA was used for weighting factors and rough MARCOS was used for the alternative selection. According to the findings, the transportation capacity factor was found to be the most important factor leading to SCM breakdowns. The most ideal supply chain management strategy has been the "collaborative supply chain management strategy." In the food manufacturing sector, the study can be considered as a roadmap in terms of preventing supply chain management breaks during the COVID-19 process and helping to ensure a sustainable production. As another theoretical and practical importance of the study, it is aimed to propose a robust, powerful, and practical decision-making model that can cope with the current uncertainties.

1. Introduction

Disasters caused by epidemics differ from other disasters due to two factors which are long-term breaks in the sectors and increased spread of the disease. Failure to control these disasters causes serious disruption to supply chains and communities. For this reason, irreparable losses may occur [1]. Breakdowns in supply chain management, especially in developing countries, cause output reduction and increase the unemployment rate [2]. According to Fortune [3], most of the companies on the Fortune 1000 list face disruptions in their supply chain management (SCM) due to COVID-19. WHO stated that in the global supply chain components, there is a great challenge to ensure the smooth supply of food and medical devices, including masks and medicines, which are vital and necessary for the treatment of COVID-19 infection [4].

Outbreaks that affect the whole world are among the reasons that cause the supply chain to break. Unlike most factors that cause supply chain disruptions, outbreaks have a low impact in the beginning. However, with its fast spread to various geographical areas, it can cause a break in the global supply chain very quickly [5]. In this context, it is obvious that the COVID-19 pandemic creates too much uncertainty and unidentified disruptions in global supply chains [6, 7]. FAO declared that the impact of COVID-19 on agriculture and supply chains occurs in terms of food supply and demand. The issue of food security is closely correlated with the supply and demand of food; thus, it has been said that they increase the risk in global food security [8].

The COVID-19 pandemic that has been characterized as an economic crisis [9], which has affected the whole world since March 2020, has been showing its effects on operations and supply chains around the world in a way that is difficult to model, measure, and predict. To stop the disease from spreading in the absence of vaccines, governments have taken nonpharmacological interventions (such as social distance policies and civil lockdowns) around the world and tried to limit human mobility. These phenomena cause serious damage to economic activities, particularly in the service and agriculture sectors deeply [10]. In other words, the COVID-19 pandemic has had an impact on many facets of global supply chains. It ranges everything from the availability of labour, raw material supply, and worker presence to product transportation and retail channel functioning.

Breakdowns in supply chain management caused by the pandemic vary from sector to sector, but the basic components act with the same phenomena for all sectors. Stank et al. [11] stated that with the measures and practices to be taken against these breaks, businesses will have the chance to compete in changing environments. They will play a key role in overcoming these obstacles. As a contrast to that, supply chain management strategies are also significant for preventing disruptions caused by breaks in supply chain management. According to Waters [12], strategic decisions, which affect the whole business, involve significant resources, carry a high level of risk, and have long-term consequences.

The supply chain strategy of an organization includes decisions, plans, policies, and cultural relationships regarding the management of all processes from procuring the raw material to the delivery of the product to the customer, and if necessary, it also includes reverse supply chain activities. While determining the supply chain strategy, it was emphasized that concepts such as cost, service level, time, quality, and flexibility should be carefully considered. In addition, the supply chain is an interconnected system with both forward and backward activities due to the intertwining of many units and operations. For achieving a competitive advantage, it is significant to select the supply chain strategy that takes customers into account as well as establishes appropriate supply and distribution networks [13]. Small- and medium-sized enterprises operating in the manufacturing industry appear as structures in which tactical activities and operational decisions are generally considered. Especially enterprises that have the goal of institutionalization should first determine their general strategies and organize their processes depending on this strategy. Otherwise, the continuity of the gains created within a certain period is not possible. Thus, it is very significant to determine the general supply chain strategy that will guide procurement decisions, materials management, and distribution planning activities [14].

In this context, there are many reasons that push the authors to investigate the problem discussed. In line with the expertise, experience, and knowledge of the decision makers, breaks in supply chain management during the COVID-19 period emerged as an important concept in terms of the continuation of production, meeting the basic needs of people, and meeting both products and services. With COVID-19, the change in business and trade environments has taken a different dimension, and it has revealed a new relationship between the efforts to perpetuate supply chains and strategies for supply chain management and enabled new models.

In terms of businesses, breaks in supply chain management and supply chain management strategy selection are considered as one of the most promising solutions for manufacturing/production and service businesses to react quickly to market conditions, prevent losses, make product and service levels sustainable, and to reduce reputational loss.

At the same time, the study is seen as a critical component in terms of bringing an effective and applicable solution to the decision-making problem involving the selection of supply chain management break factors and supply chain management strategies in the COVID-19 process in a vital area such as the manufacturing sector.

It is thought that it is valuable to work on determining the supply chain management breakage factors and supply chain management strategy with COVID-19, creating a model that will allow businesses to make self-assessments, and helping businesses to improve the production process, as well as providing businesses with a new perspective.

In the food manufacturing sector, the study can be considered as a roadmap in terms of preventing supply chain management breaks during the COVID-19 process and helping to ensure a sustainable production. It also examines the similarities and differences of the factors that cause the supply chain management break in the enterprises in the relevant sector and to what extent they can be reflected. Thus, the study provides a practical roadmap for the supply chain management breakdown factors and supply chain management strategy selection process for the food manufacturing industry during the COVID-19 era.

As another theoretical and practical importance of the study, it is aimed to propose a robust, powerful, and practical decision-making model that can cope with the current uncertainties. Therefore, in addition to contributing to the permanent solution of the relevant decision-making problem for the food manufacturing sector in the COVID-19 period, it is aimed to provide a strong and robust methodological framework to fill the theoretical gaps in the literature by using the advantages of the methods used in the study.

Thus, it will contribute to the solution of similar problems in different fields. In addition, when the results to be achieved are only related to the food sector and are evaluated within the scope of its structure suitable for comparison with other sectors, it is thought that the relevant study will make a significant contribution to the business world and literature in general, especially at the point of sustainable supply chain management and sustainable production in the COVID-19 process.

In this study, it has been investigated that COVID-19, which has been on the agenda of the whole world for about a year, causes many deaths, breaks in supply chains, collapses economies, and has many negative effects within the framework of the supply chain management. The food industry in Turkey has been affected greatly by the breaks in the supply chains during COVID-19. It has become one of the issues that needed to be dealt within the country for the effective management of the supply chain. This study's goal is to determine the most ideal supply chain strategy by prioritizing the breakdown factors of supply chain management in food manufacturing enterprises operating, which are corporates, in the Eastern Black Sea Region and have 50 or more employees. Several methodologies are used to solve prioritizing problems in the literature such as optimization models [15] and decision-making methods [16]. In this context, rough MARCOS methods based on SWARA have been used because of the complexity of the decision problem.

This study consists of six parts. SCM breakdowns and the COVID-19 pandemic impact are handled in the first part. Literature review related to SCM breakdowns due to the pandemic and studies based on SWARA and MARCOS are mentioned in the second part. Rough numbers, rough SWARA, and rough MARCOS methods are explained in the methodology section. Case studies of food firms in the East Black Sea Region are examined in the fourth part. Sensitivity and comparison analyses are executed in the fifth part. Results and suggestions are stated in the conclusion part.

2. Literature Review

Studies related to SCM breakdowns due to the pandemic process are limited and can be summarized as mentioned below.

Chou et al. [17] assessed the impact of the SARS epidemic on Taiwan airlines and detected 30 percent suspension related to international flights. Salem and Haouari [18] created a three-stage stochastic optimization model for designing the expected demand and supply based on the supply chain network. Araz et al. [19] highlighted the COVID-19 pandemic as one of the critical suspensions in the world. Queiroz et al. [20] made COVID-19-based mapping related to the impact of the epidemic on supply chains and mentioned six perspectives. These are adaptation, digitalization, preparation, recovery, fluctuation effect, and sustainability, respectively.

Ivanov [21] evaluated the spread of the pandemic on global networks for predicting both the short- and long-term effects of simulating with AnyLogic software. According to the findings factor, namely, the opening and closing dates of the facilities was obtained as the most effective for the spread. Aydın and Güner [22] examined the effect of the pandemic on the agricultural industry and food safety and stated the importance level of food safety risk for Turkey. Govindan et al. [1] utilized a fuzzy inference system (FIS)-based support system for decreasing stress levels in the society with demand management in the health supply chain, thereby breaking the COVID-19 spread chain and thus preventing the health service-related supply chain interruptions. According to the study, the first four groups (very sensitive, sensitive, a little sensitive, and normal) are determined in terms of the risk level of the immune system and past diseases (diabetics, heart disease, high blood pressure, etc.) and then the criteria are classified by using the FIS method.

Ivanov and Dolgui [23] developed a game-based theoretical model by considering the interwoven supply network for simulating the supply chain problem in the COVID-19 process and meeting the food-, communication-, and logistics-related social demand. Biswas and Das [7] detected the effect of the pandemic on the Indian manufacturing sector based on five base points (labour force deficiency, local law enforcement, lack of transportation, raw material shortage, and cash flow inadequacy). Singh et al. [24] proposed a simulation model for considering the effect of COVID-19 on logistics and suspensions that took place in food supply chains.

Wang et al. [25] detected the short-term effect of the pandemic on the supply chain breakdown for the hog market in China. Bhattacharya [26] presented a lot of propositions to cope with the global supply chain breakdowns in Singapore. Kaya [27] investigated the effects of the pandemic on OECD countries' sustainable development and evaluated the sustainability performances with the MAIRCA method.

According to the literature review, no study aims to prioritize factors leading to SCM breakdowns and selecting the most successful SCM strategy for food firms in COVID-19 and that underlined the novelty and importance of the study, especially because the COVID-19 pandemic has ushered in a new age in the world [28].

SWARA and MARCOS studies in the literature are shown in Table 1.

According to Table 1, rough SWARA-based rough MARCOS methodology is not applied for weighting factors leading to SCM breakdowns and for selecting the most successful SCM strategy for food firms during COVID-19, and that shows the originality of the study from the methodology.

3. Methodology

In this study, while determining the weights of the criteria with the rough SWARA method, the strategies will be listed with the rough MARCOS method. The methodology section consists of three parts, and they are as follows: rough set theory, rough SWARA, and rough MARCOS.

3.1. Rough Set Theory. Rough numbers convey expert decision makers' impressions in an impartial manner, and they improve the decision-making process of the decision makers [49]. Assume that D indicates the universe, K is an arbitrary

Table 1: Studies related to SWARA and MARCOS methods.

Author(s)	Methodology	Application
Valipour et al. [29]	SWARA-COPRAS	Identification and assessment of risks in deep excavation and foundation projects for big cities in Iran
Sremac et al. [30]	Rough SWARA-WASPAS	Evaluation of 3PLs
Veskovic et al. [31]	DELPHI-SWARA-MABAC	Evaluation of Bosnia and Herzegovina's railway administration system
Vockic et al. [32]	Rough SWARA-ARAS	Electric forklift selection
Zavadskas et al. [33]	Rough SWARA	Choosing of railroad carriages for local transportation requirements
Aydoğan and Özmen [34]	Rough SWARA-TODIM	Evaluating the competitiveness of countries in terms of travel
Prajapati et al. [35]	Modified SWARA-WASPAS	Weighting the solutions of reverse logistics solutions
Badi and Pamucar [36]	Grey MARCOS	Selection of suppliers for LISCO steel manufacturing firm
Chakraborty et al. [37]	D-MARCOS	Selection of suppliers in iron and steel industry
Stankovic et al. [38]	Fuzzy MARCOS	Risk analysis of traffic
Stevic et al. [39]	MARCOS	Supplier selection for Bosnia and Herzegovina's healthcare sector in terms of sustainability
Ulutaş et al. [40]	CCSD-ITARA-MARCOS	Choice of stackers in logistics
Miskic et al. [41]	SWARA-MARCOS	The classification of products into three groups
Özdağoğlu et al. [42]	Fuzzy SWARA-fuzzy MARCOS	In order to determine the importance of the criteria that airline companies should take into account in the recruitment of cabin crew and to choose the most appropriate one among the cabin crew alternatives
Taş et al. [43]	Fuzzy SWARA-MARCOS	A new combined fuzzy methodology is proposed to handle green supplier selection problem
Matic et al. [44]	IMF SWARA-rough MARCOS	To create a novel integrated multicriteria decision-making (MCDM) model for the selection of pavers for the middle category of roads
Mešić et al. [45]	MARCOS	Evaluation of the Logistics Performance Index of the Western Balkan countries
Stević et al. [46]	Fuzzy SWARA	Seven representative studies (logistics, construction industry, financial performance management, and supply chain) with different parameter structures and decision matrix sizes
Tus and Adalı [47]	Fuzzy SWARA-fuzzy MARCOS	To develop applicable and efficient methodology for green supplier selection
Puška and Stojanović [48]	Fuzzy SWARA-fuzzy MABAC, MARCOS, and CRADIS	Green supplier selection in an agrifood company

object of D, and P presents a set of t classes $\{U_1, U_2, \ldots, U_t\}$ including all the objects in D, $P = \{U_1, U_2, \ldots, U_t\}$. If these classes are sequenced as $U_1 < U_2 < \ldots < U_t$, then $\forall K \in D$, $U_q \in P$, and $1 \le q \le t$, by $P(K)$, we refer the group to which the object belongs, and the upper approximation $(\overline{\mathrm{Apr}}(U_q))$ and lower approximation $(\underline{\mathrm{Apr}}(U_q))$ of class U_q are explained as follows [50]:

$$\underline{\mathrm{Apr}}\left(U_q\right) = \left\{\frac{K \in D}{P(K)} \le U_q\right\}, \tag{1}$$

$$\overline{\mathrm{Apr}}\left(U_q\right) = \left\{\frac{K \in D}{P(K)} \ge U_q\right\}, \tag{2}$$

where U_q can be demonstrated as a rough number $\mathrm{RN}(U_q)$ and its lower limit $(\mathrm{Lim\_}(U_q))$ and upper limit $(\overline{\mathrm{Lim}}(U_q))$ can be computed as

$$\underline{\mathrm{Lim}}\left(U_q\right) = \frac{1}{M_L} \sum\left\{K \in \underline{\mathrm{Apr}}\left(U_q\right)\right\} P(K), \tag{3}$$

$$\overline{\mathrm{Lim}}\left(U_q\right) = \frac{1}{M_U} \sum\left\{K \in \overline{\mathrm{Apr}}\left(U_q\right)\right\} P(K), \tag{4}$$

$$\mathrm{RN}\left(U_q\right) = \left[\underline{\mathrm{Lim}}\left(U_q\right), \overline{\mathrm{Lim}}\left(U_q\right)\right], \tag{5}$$

where M_L and M_U are the number objects included in $\underline{\mathrm{Apr}}(U_q)$ and $\overline{\mathrm{Apr}}(U_q)$, respectively. The arithmetic operations of the two rough numbers, that is, $(\mathrm{RN}(D)$ and $\mathrm{RN}(E))$ are as follows:

$$\begin{aligned}
&\text{Addition: } \mathrm{RN}(D) + \mathrm{RN}(E) = \left[\underline{\mathrm{Lim}}(D) + \underline{\mathrm{Lim}}(E), \overline{\mathrm{Lim}}(D) + \overline{\mathrm{Lim}}(E)\right],\\
&\text{Subtraction: } \mathrm{RN}(D) - \mathrm{RN}(E) = \left[\underline{\mathrm{Lim}}(D) - \overline{\mathrm{Lim}}(E), \overline{\mathrm{Lim}}(D) - \underline{\mathrm{Lim}}(E)\right],\\
&\text{Multiplication: } \mathrm{RN}(D) \times \mathrm{RN}(E) = \left[\underline{\mathrm{Lim}}(D) \times \underline{\mathrm{Lim}}(E), \overline{\mathrm{Lim}}(D) \times \overline{\mathrm{Lim}}(E)\right],\\
&\text{Division: } \mathrm{RN}(D) \div \mathrm{RN}(E) = \left[\underline{\mathrm{Lim}}(D) \div \overline{\mathrm{Lim}}(E), \overline{\mathrm{Lim}}(D) \div \underline{\mathrm{Lim}}(E)\right].
\end{aligned} \tag{6}$$

3.2. Rough SWARA. The SWARA method, which was proposed by Keršuliene et al. [51], is frequently used in the literature as it consists of a few steps of calculation, and it needs a few pairwise comparisons. The rough SWARA method was developed by Zavadskas and his colleagues [33]. The subjectivity and uncertainty of decision makers are reduced by the combination of rough numbers with the SWARA method [33]. Simple access creation, simple data collecting, and a few processes step are all traits of rough SWARA [33]. The rough SWARA method is utilized to obtain the weights of the criteria in this study. The phase in this method is outlined as follows [33]:

Phase 1: a set of criteria is explained

Phase 2: decision makers rank the criteria with respect to the importance level

Phase 3: the preferences of experts are consolidated to achieve a group rough matrix c_j, which is represented as

$$\mathrm{RN}\left(C_j\right) = \left[c_j^L, c_j^U\right]_{1\times n}. \tag{7}$$

Phase 4: the group rough matrix is normalized by equation (9) to achieve the normalized rough matrix $(\mathrm{RN}(S_j))$, that is,

$$\mathrm{RN}\left(S_j\right) = \left[s_j^L, s_j^U\right]_{1\times n}, \tag{8}$$

where

$$\mathrm{RN}\left(S_j\right) = \begin{cases} j = 1, & [1,1],\\[2ex] j > 1, & \dfrac{\left[c_j^L, c_j^U\right]}{\max_r\left[c_r^L, c_r^U\right]}. \end{cases} \tag{9}$$

Phase 5: $\mathrm{RN}(K_j) = [k_j^L, k_j^U]_{1\times n}$ matrix is computed as

$$\mathrm{RN}\left(K_j\right) = \begin{cases} j = 1, & [1,1],\\ j > 1, & \left[s_j^L + 1, s_j^U + 1\right]. \end{cases} \tag{10}$$

Phase 6: $\mathrm{RN}(Q_j)$ (recalculated weights) matrix is computed as

$$\mathrm{RN}\left(Q_j\right) = \begin{cases} j = 1, & [1,1],\\[2ex] j > 1, & \left[\dfrac{q_{j-1}^L}{k_j^U}, \dfrac{q_{j-1}^U}{k_j^L}\right]. \end{cases} \tag{11}$$

Phase 7: the weights of criteria are computed as

$$\mathrm{RN}\left(W_j\right) = \left[w_j^L, w_j^U\right]_{1\times n} = \left[\frac{\left[q_j^L, q_j^U\right]}{\sum\left[q_j^L, q_j^U\right]}\right]. \tag{12}$$

3.3. Rough MARCOS. The foundation of the MARCOS approach is the definition of the relationship between alternatives and reference values (anti-ideal and ideal alternatives). The utility functions of the alternatives are established using the defined relationships, and a compromise ranking is then created by using anti-ideal and ideal solutions [46]. In this study, the rough MARCOS (R-MARCOS) method is utilized to rank supply chain strategies. The R-MARCOS method is helpful to decrease the uncertainty and subjectivity of the decision-makers. The phases of R-MARCOS are as follows [52]:

Phase 1: rough decision matrix $(\mathrm{RN}(V))$ is organized as follows:

$$\mathrm{RN}(V) = \left[v_{ij}^{L}, v_{ij}^{U}\right]_{m\times n}. \tag{13}$$

Phase 2: extended rough matrix $\mathrm{RN}(EV)$ is arranged by adding anti-idealRN (AID) and ideal RN (ID) solutions to the matrix.

$$\mathrm{RN}(\mathrm{AID}) = \left[v_{\mathrm{aid}}^{L}, v_{\mathrm{aid}}^{U}\right] = \begin{cases} \min\limits_{i} \left[v_{ij}^{L}, v_{ij}^{U}\right], & \text{if } j \in B, \\ \max\limits_{i} \left[v_{ij}^{L}, v_{ij}^{U}\right], & \text{if } j \in C, \end{cases} \tag{14}$$

$$\mathrm{RN}(\mathrm{ID}) = \left[v_{\mathrm{id}}^{L}, v_{\mathrm{id}}^{U}\right] = \begin{cases} \max\limits_{i} \left[v_{ij}^{L}, v_{ij}^{U}\right], & \text{if } j \in B, \\ \min\limits_{i} \left[v_{ij}^{L}, v_{ij}^{U}\right], & \text{if } j \in C. \end{cases} \tag{15}$$

In equations (14) and (15), B and C indicate beneficial and nonbeneficial criteria.

Phase 3: rough normalized matrix $\mathrm{RN}(T)$ is created by using equations (17) and (18).

$$\mathrm{RN}(T) = \left[t_{\mathrm{ij}}^{L}, t_{\mathrm{ij}}^{U}\right]_{m\times n}, \tag{16}$$

$$\left[t_{ij}^{L}, t_{ij}^{U}\right] = \left[\frac{v_{ij}^{L}}{v_{id}^{U}}, \frac{v_{ij}^{U}}{v_{id}^{U}}\right] \text{if } j \in B, \tag{17}$$

$$\left[t_{\mathrm{ij}}^{L}, t_{\mathrm{ij}}^{U}\right] = \left[\frac{v_{id}^{L}}{v_{ij}^{U}}, \frac{v_{id}^{L}}{v_{ij}^{L}}\right] \text{if } \ j \in C. \tag{18}$$

Phase 4: rough weighted normalized matrix $\mathrm{RN}(E)$ is computed by using the following equation:

$$\mathrm{RN}(E) = \left[e_{\mathrm{ij}}^{L}, e_{\mathrm{ij}}^{U}\right] = \left[t_{\mathrm{ij}}^{L} \times w_{j}^{L}, t_{\mathrm{ij}}^{U} \times w_{j}^{U}\right]. \tag{19}$$

Phase 5: $RN(Z)$ is computed by using the equation as follows:

$$\mathrm{RN}(Z) = \left[z_{i}^{L}, z_{i}^{U}\right] = \sum_{j=1}^{n} \left[e_{\mathrm{ij}}^{L}, e_{\mathrm{ij}}^{U}\right]. \tag{20}$$

Phase 6: rough utility degrees of alternatives $\mathrm{RN}(Y_i^-)$ and $\mathrm{RN}(Y_i^+)$ are calculated as

$$\mathrm{RN}(Y_i^-) = \left[y_i^{-L}, y_i^{-U}\right] = \left[\frac{z_i^L}{z_{\mathrm{aid}}^U}, \frac{z_i^U}{z_{\mathrm{aid}}^L}\right], \tag{21}$$

$$\mathrm{RN}(Y_i^+) = \left[y_i^{+L}, y_i^{+U}\right] = \left[\frac{z_i^L}{z_{id}^U}, \frac{z_i^U}{z_{id}^L}\right]. \tag{22}$$

Phase 7: rough utility degrees $(\mathrm{RN}(Y_i^-)$ and $\mathrm{RN}(Y_i^+))$ are then converted into crisp Y_i^- and Y_i^+.

$$Y_i^- = \frac{y_i^{-L} + y_i^{-U}}{2}, \tag{23}$$

$$Y_i^+ = \frac{y_i^{+L} + y_i^{+U}}{2}. \tag{24}$$

Phase 8: the utility functions in relation to the anti-ideal $f(Y_i^-)$ and ideal $f(Y_i^+)$ solutions are computed by using equations (25) and (26), respectively.

$$f(Y_i) = \frac{Y_i^+ + Y_i^-}{1 + \left(1 - f(Y_i^+)/f(Y_i^+)\right) + \left(1 - f(Y_i^-)/f(Y_i^-)\right)}, \tag{25}$$

where

$$f(Y_i^-) = \frac{Y_i^+}{Y_i^+ + Y_i^-}, \tag{26}$$

$$f(Y_i^+) = \frac{Y_i^-}{Y_i^+ + Y_i^-}. \tag{27}$$

Phase 9: the alternatives are then ranked from the maximum to the minimum utility function.

4. Application

In this study, it is aimed to prioritize the factors leading to SCM breakdowns and choosing the most successful SCM strategy in the COVID-19 process. The SCM strategies considered in the assessment in this study are as follows: lean supply chain management strategy (LSCMS), agile supply chain management strategy (ASCMS), collaborative supply chain management strategy (CSCMS), vertical integration strategy-based on lean supply chain axis (VIS), and lean supply chain outsourcing axis-based strategy (LSCOAS). These SCM strategies are evaluated with respect to their performance under the criteria leading to SCM breakdowns.

The factors considered in the evaluation of this study are existence of skilled workforce (ESW), business dispute (BD), local laws-related incentives (LLRI), cash flow scarcity in the manufacturing sector (CFSMS), supplier bankruptcy (SB), alternative supplier capacity and flexibility (ASCF), lack of risks related to pandemic (COVID-19), war, terrorism, and force majeure (LRRPWTFM), transportation capacity (TC), and level of raw material procurement (LRMP). Factors and strategies were determined according to the literature review and experts (academicians, managers, and public authorities) decisions. The Eastern Black Sea Region of Turkey provided the data for this study. First, the six major company managers ranked the factors from most important to least important. The decision makers consisted of 6 experts in total, including the operation manager (2), the process manager (2), the purchasing manager (1), and the general manager of the business (1) working in the field of food manufacturing.

The ranking of factors according to the preferences of managers (M) is shown in Table 2.

The weights of the factors are found by using the rough SWARA method and the data in Tables 2 and 3 present the findings of the rough SWARA. Figure 1 shows the weight of the factors. First, the rankings of the factors are consolidated to achieve a group rough matrix by using equations (3) and (4). The ESW factor is as an example to illustrate the calculation as follows:

$$\mathrm{ESW} = \{2, 5, 5, 3, 6, 5\}$$

$$\underline{\mathrm{Lim}}(2) = 2,$$

$$\overline{\mathrm{Lim}}(2) = \frac{(2+5+5+3+6+5)}{6} = 4.333$$

$$\underline{\mathrm{Lim}}(5) = \frac{(2+5+5+3+5)}{5} = 4,$$

$$\overline{\mathrm{Lim}}(5) = \frac{(5+5+6+5)}{4} = 5.25$$

$$\underline{\mathrm{Lim}}(3) = \frac{(2+3)}{2} = 2.5,$$

$$\overline{\mathrm{Lim}}(3) = \frac{(5+5+3+6+5)}{5} = 4.8$$

$$\underline{\mathrm{Lim}}(6) = \frac{(2+5+5+3+5+6)}{6} = 4.333,$$

$$\overline{\mathrm{Lim}}(6) = 6$$

$$\mathrm{RN}\left(\mathrm{ESW}_1\right) = [2, 4.333]$$

$$\mathrm{RN}\left(\mathrm{ESW}_2\right) = [4, 5.25]$$

$$\mathrm{RN}\left(\mathrm{ESW}_3\right) = [4, 5.25]$$

$$\mathrm{RN}\left(\mathrm{ESW}_4\right) = [2.5, 4.8]$$

$$\mathrm{RN}\left(\mathrm{ESW}_5\right) = [4.333, 6]$$

$$\mathrm{RN}\left(\mathrm{ESW}_6\right) = [4, 5.25]$$

$$\mathrm{ESW}^L = \frac{2+4+4+2.5+4.333+4}{6} = 3.472$$

$$\mathrm{ESW}^U = \frac{4.333+5.25+5.25+4.8+6+5.25}{6} = 5.147. \tag{28}$$

The same operations are performed for other factors. Then, the normalization process is performed with equation (12). The ESW factor is taken as an example to illustrate the calculation as follows:

$$\mathrm{RN}\left(S_{\mathrm{ESW}}\right) = \left[\frac{3.472}{7.956}, \frac{5.147}{4.444}\right] = [0.436, 1.158]. \tag{29}$$

The same operation is performed for other factors. After the normalization process, the $\mathrm{RN}(K_j)$ value is found by using equation (13). The ESW factor is taken as an example to illustrate the calculation as follows:

$$\mathrm{RN}\left(K_{\mathrm{ESW}}\right) = [1+0.436, 1+1.158] = [1.436, 2.158]. \tag{30}$$

After these calculations, the $\mathrm{RN}(Q_j)$ value is obtained by using equation (14). The ESW factor is taken as an example to illustrate the calculation that follows:

$$\mathrm{RN}\left(Q_{\mathrm{ESW}}\right) = \left[\frac{1.277}{2.158}, \frac{2.216}{1.436}\right] = [0.592, 1.543]. \tag{31}$$

In the final step, the weights of the factors are calculated by using equation (15). The ESW factor is taken as an example to indicate the computation.

$$\mathrm{RN}\left(w_{\mathrm{ESW}}\right) = \left[\frac{0.592}{(1+0.783+1.543+1.539+1.704+1.722+1.710+1.795+1.743)}, \frac{1.543}{(1+0.451+0.592+0.573+0.567+0.572+0.524+0.553+0.547)}\right] \tag{32}$$
$$= [0.044, 0.287].$$

Table 2: The ranking of factors.

Factors	Managers					
	M1	M2	M3	M4	M5	M6
ESW	2	5	5	3	6	5
BD	6	8	7	4	4	2
LLRI	5	1	6	1	7	3
CFSMS	8	2	3	5	1	1
SB	4	3	9	2	3	8
ASCF	3	7	4	9	2	6
LRRPWTFM	1	6	8	8	9	4
TC	9	4	2	6	8	7
LRMP	7	9	1	7	5	9

Table 3: The rough SWARA findings.

Factors	w_j^L	w_j^U	w_j	Ranking
CFSMS	0.074	0.186	0.130	8
LLRI	0.033	0.146	0.089	9
ESW	0.044	0.287	0.165	6
SB	0.042	0.286	0.164	7
BD	0.042	0.317	0.179	4
ASCF	0.042	0.320	0.181	3
LRRPWTFM	0.039	0.318	0.178	5
TC	0.041	0.334	0.187	1
LRMP	0.040	0.324	0.182	2

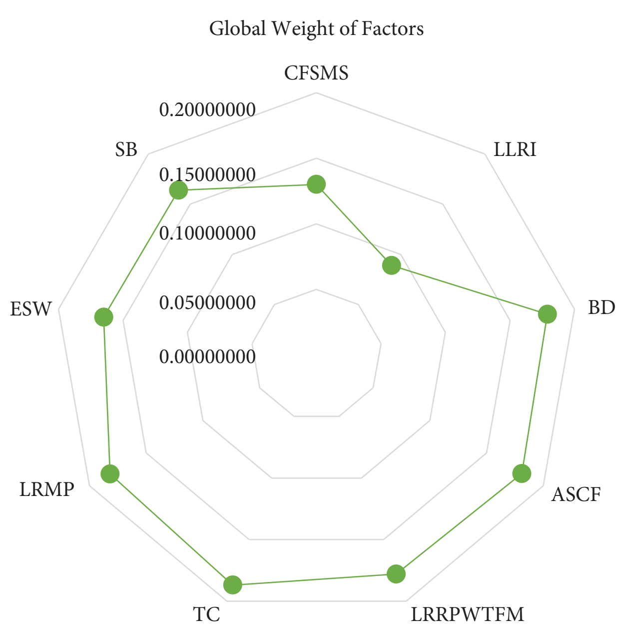

Figure 1: Weight of the factors.

Table 3 shows the weights of the factors.

By taking the arithmetic mean of the w_j^L and w_j^U values, it can be determined which factor is more important by finding the crisp weights of the factors. w_j values have shown that the most significant criterion is TC with the value of 0.187. On the other hand, the criterion of LLRI is determined as the least significant with the value of 0.089. Managers assigned values between 1 (the lowest) and 9 (the highest) to each factor. The preferences of managers are consolidated by using equations (3) and (4) to organize a rough decision matrix. The ESW factor for the LSCMS strategy is taken as an example to indicate these calculations.

$$\text{LSCMS}_{\text{ESW}} = \{3, 5, 3, 2, 3, 2\}$$

$$\begin{aligned}
&\underline{\text{Lim}}(3) = \frac{(3+3+2+3+2)}{5} = 2.6,\\
&\overline{\text{Lim}}(3) = \frac{(3+5+3+3)}{4} = 3.5\\
&\underline{\text{Lim}}(5) = \frac{(3+5+3+2+3+2)}{6} = 3,\\
&\overline{\text{Lim}}(5) = 5\\
&\underline{\text{Lim}}(2) = 2,\\
&\overline{\text{Lim}}(2) = \frac{(3+5+3+2+3+2)}{6} = 3\\
&\text{RN}(\text{LSCMS}_1) = [2.6, 3.5]\\
&\text{RN}(\text{LSCMS}_2) = [3, 5]\\
&\text{RN}(\text{LSCMS}_3) = [2.6, 3.5]\\
&\text{RN}(\text{LSCMS}_4) = [2, 3]\\
&\text{RN}(\text{LSCMS}_5) = [2.6, 3.5]\\
&\text{RN}(\text{LSCMS}_6) = [2, 3]\\
&\text{LSCM}^L = \frac{2.6+3+2.6+2+2.6+2}{6} = 2.467\\
&\text{LSCM}^U = \frac{3.5+5+3.5+3+3.5+3}{6} = 3.583.
\end{aligned} \tag{33}$$

The same operations are performed in other strategies and other factors. The rough decision matrix is shown in Table 4.

Anti-ideal and perfect solutions are added to the matrix to create the extended rough matrix. This matrix is shown in Table 5.

The extended rough matrix is transformed into the rough normalized matrix by using equations (17) and (18). Table 6 shows the rough normalized matrix.

The ESW factor for the LSCMS strategy will be taken as an example to illustrate this calculation. This factor is a beneficial factor, so equation (17) will be used.

$$\left[t_{11}^{L}, t_{11}^{U}\right] = \left[\frac{v_{11}^{L}}{v_{11}^{U}}, \frac{v_{11}^{U}}{v_{11}^{U}}\right] = \left[\frac{2.467}{4.881}, \frac{3.583}{4.881}\right] = [0.505, 0.734]. \tag{34}$$

The rough weighted matrix (Table 7) is created by multiplying (equation (19)) the rough normalized values with the rough weights of the factors. The ESW factor for the LSCMS strategy is taken as an example to illustrate this calculation.

$$\mathrm{RN}(E) = \left[e_{11}^{L}, e_{11}^{U}\right] = \left[t_{11}^{L} \times w_{1}^{L}, t_{11}^{U} \times w_{1}^{U}\right] = [0.505 \times 0.044, 0.734 \times 0.287] = [0.022, 0.211]. \tag{35}$$

The findings of the rough MARCOS technique are derived using the equations (20)–(27). Table 8 ranks the strategies based on these findings. The LSCMS strategy is taken as an example to illustrate these calculations.

$$\mathrm{RN}(Z) = \left[z_{1}^{L}, z_{1}^{U}\right] = \sum_{j=1}^{n} \left[e_{ij}^{L}, e_{ij}^{U}\right] = \begin{bmatrix} (0.022 + 0.026 + 0.021 + 0.039 + 0.017 + 0.023 + 0.018 + 0.027 + 0.023), \\ (0.211 + 0.303 + 0.134 + 0.176 + 0.278 + 0.280 + 0.274 + 0.321 + 0.310) \end{bmatrix} = [0.216, 2.287]$$

$$\mathrm{RN}\left(Y_{1}^{-}\right) = \left[y_{1}^{-L}, y_{1}^{-U}\right] = \left[\frac{z_{1}^{L}}{z_{aid}^{U}}, \frac{z_{1}^{U}}{z_{aid}^{L}}\right] = \left[\frac{0.216}{1.929}, \frac{2.287}{0.186}\right] = [0.112, 12.296]$$

$$\mathrm{RN}\left(Y_{1}^{+}\right) = \left[y_{1}^{+L}, y_{1}^{+U}\right] = \left[\frac{z_{1}^{L}}{z_{id}^{U}}, \frac{z_{1}^{U}}{z_{id}^{L}}\right] = \left[\frac{0.216}{2.518}, \frac{2.287}{0.254}\right] = [0.086, 9.004]$$

$$Y_{1}^{-} = \frac{y_{1}^{-L} + y_{1}^{-U}}{2} = \frac{0.112 + 12.296}{2} = 6.204$$

$$Y_{1}^{+} = \frac{y_{1}^{+L} + y_{1}^{+U}}{2} = \frac{0.086 + 9.004}{2} = 4.545$$

$$f\left(Y_{1}^{-}\right) = \frac{Y_{1}^{+}}{Y_{1}^{+} + Y_{1}^{-}} = \frac{4.545}{6.204 + 4.545} = 0.423$$

$$f\left(Y_{1}^{+}\right) = \frac{Y_{1}^{-}}{Y_{1}^{+} + Y_{1}^{-}} = \frac{6.204}{6.204 + 4.545} = 0.577$$

$$f\left(Y_{1}\right) = \frac{Y_{1}^{+} + Y_{1}^{-}}{1 + \left(1 - f\left(Y_{1}^{+}\right)/f\left(Y_{1}^{+}\right)\right) + \left(1 - f\left(Y_{1}^{-}\right)/f\left(Y_{1}^{-}\right)\right)} = \frac{6.204 + 4.545}{1 + (1 - 0.577/0.577) + (1 - 0.423/0.423)} = 3.471. \tag{36}$$

The strategies are ranked as follows according to the findings of the rough MARCOS: CSCMS, LSCMS, LSCOAS, VIS, and ASCMS. By standing first, CSCMS shows its importance in providing cost benefits to businesses that implement it as a strategy, as it allows for the direction of their manpower, capital, and time to their core capabilities and operations while outsourcing the noncore activities and functions to other logistics service providers. The first place in the ranking of the strategy is also attributed to its perceived value, especially during the COVID-19 pandemic, regarding the expansion of the service area of the relevant sector, the expansion of the location served, the reduction

Table 4: The rough decision matrix.

Strategies	Factors								
	ESW	BD	LLRI	CFSMS	SB	ASCF	LRRPWTFM	TC	LRMP
LSCMS	(2.467, 3.583)	(2.611, 4.111)	(3.308, 4.750)	(2.667, 3.583)	(2.656, 6.478)	(2.681, 4.320)	(3.045, 5.822)	(3.681, 5.320)	(3.861, 6.547)
ASCMS	(2.764, 3.939)	(3.117, 3.917)	(2.583, 4.500)	(3.658, 5.722)	(3.295, 6.214)	(3.495, 4.889)	(4.117, 6.417)	(4.061, 5.236)	(2.875, 5.314)
CSCMS	(2.706, 4.872)	(2.500, 3.500)	(3.153, 5.172)	(3.522, 5.278)	(3.761, 6.661)	(2.878, 4.472)	(4.250, 6.750)	(3.495, 4.889)	(4.556, 6.845)
VIS	(2.428, 4.881)	(3.500, 4.500)	(2.569, 4.361)	(2.528, 4.878)	(3.928, 6.556)	(2.928, 4.789)	(4.500, 6.500)	(3.211, 5.072)	(3.811, 6.044)
LSCOAS	(3.111, 4.506)	(4.461, 5.861)	(3.461, 4.861)	(3.478, 5.811)	(2.583, 5.633)	(2.978, 4.944)	(3.334, 6.067)	(4.417, 5.533)	(3.694, 6.017)

Table 5: Extended rough matrix.

Strategies	Factors								
	ESW	BD	LLRI	CFSMS	SB	ASCF	LRRPWTFM	TC	LRMP
Anti-ideal	(2.428, 3.583)	(4.461, 5.861)	(2.569, 4.361)	(3.658, 5.811)	(3.928, 6.661)	(2.681, 4.320)	(3.045, 5.822)	(3.211, 4.889)	(2.875, 5.314)
LSCMS	(2.467, 3.583)	(2.611, 4.111)	(3.308, 4.750)	(2.667, 3.583)	(2.656, 6.478)	(2.681, 4.320)	(3.045, 5.822)	(3.681, 5.320)	(3.861, 6.547)
ASCMS	(2.764, 3.939)	(3.117, 3.917)	(2.583, 4.500)	(3.658, 5.722)	(3.295, 6.214)	(3.495, 4.889)	(4.117, 6.417)	(4.061, 5.236)	(2.875, 5.314)
CSCMS	(2.706, 4.872)	(2.500, 3.500)	(3.153, 5.172)	(3.522, 5.278)	(3.761, 6.661)	(2.878, 4.472)	(4.250, 6.750)	(3.495, 4.889)	(4.556, 6.845)
VIS	(2.428, 4.881)	(3.500, 4.500)	(2.569, 4.361)	(2.528, 4.878)	(3.928, 6.556)	(2.928, 4.789)	(4.500, 6.500)	(3.211, 5.072)	(3.811, 6.044)
LSCOAS	(3.111, 4.506)	(4.461, 5.861)	(3.461, 4.861)	(3.478, 5.811)	(2.583, 5.633)	(2.978, 4.944)	(3.334, 6.067)	(4.417, 5.533)	(3.694, 6.017)
Ideal	(3.111, 4.881)	(2.500, 3.500)	(3.461, 5.172)	(2.528, 4.806)	(2.583, 5.633)	(3.495, 4.944)	(4.500, 6.750)	(4.417, 5.533)	(4.556, 6.845)

Table 6: Rough normalized matrix.

Strategies	Factors								
	ESW	BD	LLRI	CFSMS	SB	ASCF	LRRPWTFM	TC	LRMP
Anti-ideal	(0.497, 0.734)	(0.427, 0.560)	(0.497, 0.843)	(0.435, 0.691)	(0.388, 0.658)	(0.542, 0.874)	(0.451, 0.863)	(0.580, 0.884)	(0.420, 0.776)
LSCMS	(0.505, 0.734)	(0.608, 0.957)	(0.640, 0.918)	(0.526, 0.948)	(0.399, 0.973)	(0.542, 0.874)	(0.451, 0.863)	(0.665, 0.962)	(0.564, 0.956)
ASCMS	(0.566, 0.807)	(0.638, 0.802)	(0.499, 0.870)	(0.442, 0.691)	(0.416, 0.784)	(0.707, 0.989)	(0.610, 0.951)	(0.734, 0.946)	(0.420, 0.776)
CSCMS	(0.554, 0.998)	(0.714, 1.000)	(0.610, 1.000)	(0.479, 0.718)	(0.388, 0.687)	(0.582, 0.905)	(0.630, 1.000)	(0.632, 0.884)	(0.666, 1.000)
VIS	(0.497, 1.000)	(0.556, 0.714)	(0.497, 0.843)	(0.518, 1.000)	(0.394, 0.658)	(0.592, 0.969)	(0.667, 0.963)	(0.580, 0.917)	(0.557, 0.883)
LSCOAS	(0.637, 0.923)	(0.427, 0.560)	(0.669, 0.940)	(0.435, 0.727)	(0.459, 1.000)	(0.602, 1.000)	(0.494, 0.899)	(0.798, 1.000)	(0.540, 0.879)
Ideal	(0.637, 1.000)	(0.714, 1.000)	(0.669, 1.000)	(0.526, 1.000)	(0.459, 1.000)	(0.707, 1.000)	(0.667, 1.000)	(0.798, 1.000)	(0.666, 1.000)

Table 7: Rough weighted normalized matrix.

Strategies	Factors								
	ESW	BD	LLRI	CFSMS	SB	ASCF	LRRPWTFM	TC	LRMP
Anti-ideal	(0.022, 0.211)	(0.018, 0.178)	(0.016, 0.123)	(0.032, 0.129)	(0.016, 0.188)	(0.023, 0.280)	(0.018, 0.274)	(0.024, 0.295)	(0.017, 0.251)
LSCMS	(0.022, 0.211)	(0.026, 0.303)	(0.021, 0.134)	(0.039, 0.176)	(0.017, 0.278)	(0.023, 0.280)	(0.018, 0.274)	(0.027, 0.321)	(0.023, 0.310)
ASCMS	(0.025, 0.232)	(0.027, 0.254)	(0.016, 0.127)	(0.033, 0.129)	(0.017, 0.224)	(0.030, 0.316)	(0.024, 0.302)	(0.030, 0.316)	(0.017, 0.251)
CSCMS	(0.024, 0.286)	(0.030, 0.317)	(0.020, 0.146)	(0.035, 0.134)	(0.016, 0.196)	(0.024, 0.290)	(0.025, 0.318)	(0.026, 0.295)	(0.027, 0.324)
VIS	(0.022, 0.287)	(0.023, 0.226)	(0.016, 0.123)	(0.038, 0.186)	(0.017, 0.188)	(0.025, 0.310)	(0.026, 0.306)	(0.024, 0.306)	(0.022, 0.286)
LSCOAS	(0.028, 0.265)	(0.018, 0.178)	(0.022, 0.137)	(0.032, 0.135)	(0.019, 0.286)	(0.025, 0.320)	(0.019, 0.286)	(0.033, 0.334)	(0.022, 0.285)
Ideal	(0.028, 0.287)	(0.030, 0.317)	(0.022, 0.146)	(0.039, 0.186)	(0.019, 0.286)	(0.030, 0.320)	(0.026, 0.318)	(0.033, 0.334)	(0.027, 0.324)

Table 8: The findings of rough MARCOS.

Strategies	Results								
	RN (Z)	RN (Y_i^-)	RN (Y_i^+)	Y_i^-	Y_i^+	$f(Y_i^-)$	$f(Y_i^+)$	$f(Y_i)$	Rankings
Anti-ideal	(0.186, 1.929)								
LSCMS	(0.216, 2.287)	(0.112, 12.296)	(0.086, 9.004)	6.204	4.545	0.423	0.577	3.471	2
ASCMS	(0.219, 2.151)	(0.114, 11.565)	(0.087, 8.469)	5.840	4.278	0.423	0.577	3.267	5
CSCMS	(0.227, 2.306)	(0.118, 12.398)	(0.090, 9.079)	6.258	4.585	0.423	0.577	3.501	1
VIS	(0.213, 2.218)	(0.110, 11.925)	(0.085, 8.732)	6.018	4.409	0.423	0.577	3.367	4
LSCOAS	(0.218, 2.226)	(0.113, 11.968)	(0.087, 8.764)	6.041	4.426	0.423	0.577	3.380	3
Ideal	(0.254, 2.518)								

and sharing of the total costs, increasing the level and quality of service, as well as creating a common power.

Another important strategy in manufacturing enterprises is LSCMS. This is because enterprises can only minimize waste, reduce stocks, and ensure an effective material flow through LSCMS, especially during the COVID-19 period. In other words, reducing each resource used in all operations as much as possible is the strategic element that creates added value that all businesses focus on.

5. Sensitivity and Comparative Analysis

5.1. Sensitivity Analysis. In this part of the paper, we have analysed the effect of changing the three most important criteria C8-TC, C9-LRMP, and C6-ASCF on the ranks because it is a higher probability that the most essential criteria can have an influence on the ranking alternatives. For the creation of scenarios with simulated criteria weights (Table 9), we have used the following equation:

$$W_{n\beta} = \left(1 - W_{n\alpha}\right) \frac{W_\beta}{\left(1 - W_n\right)}. \tag{37}$$

In equation (37), $W_{n\beta}$ represents the corrected values of all criteria values and $W_{n\alpha}$ indicates the lowered values of the criterion TC in scenarios S1–S10, LRMP in scenarios S11–S20, and ASCF in scenarios S21–S30. W_β is the original value of each considered criterion, and W_n is the initial value of the criterion TC in scenarios S1–S10, LRMP in scenarios S11–S20, and ASCF in scenarios S21–S30.

The value of the criterion TC was lowered by 5% in the first scenario, while the values of the other criteria were modified accordingly using the equation mentioned above. The value of the TC criterion is 10% less in each of the S2–S10 scenarios, so in scenario S10, it has a value of only (0.006, 0.050) (reduced by 95%). The same procedure is followed in scenarios S11–S20 for the LRMP criterion, and in scenarios S21–S30 for the ASCF criterion which means that scenarios S1–10 represent reduction of the most important criterion (TC) in the range 5–95%, and scenarios S11–S20 represent the reduction of LRMP criterion. Scenarios S21–S30 represent the reduction of the ASCF criterion.

The output of the model created from the newly created 30 criterion weight vectors is presented in Figure 2. A sensitivity analysis was formed in terms of 30 scenarios with simulated criteria weights.

According to Figure 2, only the strategies of VIS and LSCOAS changed their position (VIS from third to fourth place) in the total number of 10 scenarios (S4–S10, S27, S29, and S30). Considering such results, we may draw the conclusion that the model is not extremely sensitive to the significance of the criteria and that the shift in the importance of the criteria values does not have a significant effect.

5.2. Comparative Analysis. Rough ARAS [53], rough WASPAS [54], and rough SAW [55] methods were applied to determine whether the rough MARCOS method achieved the correct results. Table 10 shows the results of the rough MCDM methods. Figure 3 refers to rough number values in a comparative analysis with the mentioned methods.

As seen in Table 10, the ranking of the strategies was the same in rough MARCOS and rough WASPAS methods. Likewise, the results of the rough SAW and rough ARAS methods are the same. The Spearman correlation coefficient between the results of the rough MARCOS-rough ARAS methods was determined as 0.9. In addition, the Spearman correlation coefficient between the results of the rough MARCOS and rough SAW methods was determined as 0.9 since the results of the rough SAW method were the same as the results of the rough ARAS method. As can be seen, there is a high correlation between the results of the proposed rough MARCOS method and the results of other rough MCDM methods. Therefore, it has been confirmed that the proposed rough MARCOS method achieved accurate results. As seen in Figure 3, rough MARCOS has the smallest range, while the rough values in rough ARAS have the largest range (0.053–14.380), as can be seen by observing the lower and upper limits of the rough number. The rough numbers and rough WASPAS have a relatively small range (0.496–2.937), and for rough SAW it is (0.213–3.572). The values of rough numbers may vary depending on the methodology itself, but the results obtained using the integrated rough SWARA and rough MARCOS model have been verified, as can be seen from their ranks and the calculated Spearman's coefficient (SCC).

Also, the Spearman correlation coefficient SCC [56] was made between rough MARCOS and the other methods. SCC as 0.90 was calculated between rough MARCOS, rough ARAS, and rough SAW. Finally, the highest coefficient as 1.00 showing the same alternative ranking between rough MARCOS and rough WASPAS was acquired.

Table 9: The weights of new simulated criteria in a sensitivity analysis.

	W1	W2	W3	W4	W5	W6	W7	W8	W9
SN1	(0.045, 0.288)	(0.043, 0.318)	(0.034, 0.146)	(0.076, 0.186)	(0.043, 0.287)	(0.043, 0.321)	(0.040, 0.319)	(0.039, 0.317)	(0.041, 0.325)
SN2	(0.047, 0.289)	(0.045, 0.319)	(0.035, 0.147)	(0.080, 0.187)	(0.045, 0.288)	(0.045, 0.322)	(0.042, 0.320)	(0.035, 0.284)	(0.043, 0.326)
SN3	(0.050, 0.290)	(0.047, 0.320)	(0.037, 0.148)	(0.083, 0.188)	(0.047, 0.289)	(0.047, 0.323)	(0.044, 0.321)	(0.031, 0.251)	(0.045, 0.327)
SN4	(0.052, 0.291)	(0.049, 0.322)	(0.039, 0.148)	(0.087, 0.189)	(0.049, 0.290)	(0.049, 0.325)	(0.046, 0.323)	(0.027, 0.217)	(0.047, 0.329)
SN5	(0.054, 0.293)	(0.051, 0.323)	(0.040, 0.149)	(0.091, 0.190)	(0.051, 0.292)	(0.051, 0.326)	(0.048, 0.324)	(0.023, 0.184)	(0.049, 0.330)
SN6	(0.056, 0.294)	(0.054, 0.324)	(0.042, 0.149)	(0.094, 0.190)	(0.054, 0.293)	(0.054, 0.328)	(0.050, 0.325)	(0.018, 0.150)	(0.051, 0.332)
SN7	(0.058, 0.295)	(0.056, 0.326)	(0.044, 0.150)	(0.098, 0.191)	(0.056, 0.294)	(0.056, 0.329)	(0.052, 0.327)	(0.014, 0.117)	(0.053, 0.333)
SN8	(0.061, 0.296)	(0.058, 0.327)	(0.045, 0.151)	(0.102, 0.192)	(0.058, 0.295)	(0.058, 0.330)	(0.054, 0.328)	(0.010, 0.084)	(0.055, 0.334)
SN9	(0.063, 0.297)	(0.060, 0.0329)	(0.047, 0.151)	(0.106, 0.193)	(0.060, 0.296)	(0.060, 0.332)	(0.056, 0.330)	(0.006, 0.050)	(0.057, 0.336)
SN10	(0.065, 0.299)	(0.062, 0.330)	(0.049, 0.152)	(0.109, 0.194)	(0.062, 0.298)	(0.062, 0.333)	(0.058, 0.331)	(0.002, 0.017)	(0.059, 0.337)
SN11	(0.045, 0.288)	(0.043, 0.318)	(0.034, 0.146)	(0.076, 0.186)	(0.043, 0.287)	(0.043, 0.321)	(0.040, 0.319)	(0.042, 0.335)	(0.038, 0.308)
SN12	(0.047, 0.289)	(0.045, 0.319)	(0.035, 0.147)	(0.079, 0.187)	(0.045, 0.288)	(0.045, 0.322)	(0.042, 0.320)	(0.044, 0.336)	(0.034, 0.275)
SN13	(0.049, 0.290)	(0.047, 0.320)	(0.037, 0.148)	(0.083, 0.188)	(0.047, 0.289)	(0.047, 0.323)	(0.044, 0.321)	(0.046, 0.337)	(0.030, 0.243)
SN14	(0.051, 0.291)	(0.049, 0.322)	(0.039, 0.148)	(0.086, 0.189)	(0.049, 0.290)	(0.049, 0.325)	(0.046, 0.323)	(0.048, 0.339)	(0.026, 0.211)
SN15	(0.053, 0.292)	(0.051, 0.323)	(0.040, 0.149)	(0.090, 0.189)	(0.051, 0.291)	(0.051, 0.326)	(0.047, 0.324)	(0.050, 0.340)	(0.022, 0.178)
SN16	(0.056, 0.294)	(0.053, 0.324)	(0.042, 0.149)	(0.094, 0.190)	(0.053, 0.293)	(0.053, 0.327)	(0.049, 0.325)	(0.052, 0.342)	(0.018, 0.146)
SN17	(0.041, 0.295)	(0.039, 0.326)	(0.030, 0.150)	(0.068, 0.191)	(0.039, 0.294)	(0.039, 0.329)	(0.036, 0.327)	(0.038, 0.343)	(0.014, 0.113)
SN18	(0.060, 0.296)	(0.057, 0.327)	(0.045, 0.151)	(0.101, 0.192)	(0.057, 0.295)	(0.057, 0.330)	(0.053, 0.328)	(0.056, 0.344)	(0.010, 0.081)
SN19	(0.062, 0.297)	(0.059, 0.328)	(0.046, 0.151)	(0.104, 0.193)	(0.059, 0.296)	(0.059, 0.331)	(0.055, 0.329)	(0.058, 0.346)	(0.006, 0.049)
SN20	(0.064, 0.298)	(0.061, 0.330)	(0.048, 0.152)	(0.108, 0.193)	(0.061, 0.297)	(0.061, 0.333)	(0.057, 0.331)	(0.060, 0.347)	(0.002, 0.016)
SN21	(0.045, 0.288)	(0.043, 0.318)	(0.034, 0.146)	(0.076, 0.186)	(0.043, 0.287)	(0.040, 0.304)	(0.040, 0.319)	(0.042, 0.335)	(0.041, 0.325)
SN22	(0.047, 0.289)	(0.045, 0.319)	(0.0035, 0.147)	(0.079, 0.187)	(0.045, 0.288)	(0.036, 0.272)	(0.042, 0.320)	(0.044, 0.336)	(0.043, 0.326)
SN23	(0.049, 0.29)	(0.047, 0.320)	(0.037, 0.148)	(0.083, 0.188)	(0.047, 0.289)	(0.032, 0.240)	(0.044, 0.321)	(0.046, 0.338)	(0.045, 0.328)
SN24	(0.051, 0.291)	(0.049, 0.322)	(0.038, 0.148)	(0.086, 0.189)	(0.049, 0.290)	(0.027, 0.208)	(0.045, 0.323)	(0.048, 0.339)	(0.047, 0.329)
SN25	(0.053, 0.293)	(0.051, 0.323)	(0.040, 0.149)	(0.090, 0.190)	(0.051, 0.292)	(0.023, 0.176)	(0.047, 0.324)	(0.050, 0.341)	(0.048, 0.330)
SN26	(0.055, 0.294)	(0.053, 0.325)	(0.042, 0.150)	(0.093, 0.190)	(0.053, 0.293)	(0.019, 0.144)	(0.049, 0.326)	(0.052, 0.342)	(0.050, 0.332)
SN27	(0.057, 0.295)	(0.055, 0.326)	(0.043, 0.150)	(0.097, 0.191)	(0.055, 0.294)	(0.015, 0.112)	(0.051, 0.327)	(0.054, 0.344)	(0.052, 0.333)
SN28	(0.060, 0.296)	(0.057, 0.327)	(0.045, 0.151)	(0.100, 0.192)	(0.057, 0.295)	(0.011, 0.080)	(0.053, 0.328)	(0.055, 0.345)	(0.054, 0.335)
SN29	(0.062, 0.298)	(0.059, 0.329)	(0.046, 0.151)	(0.104, 0.193)	(0.059, 0.297)	(0.006, 0.048)	(0.055, 0.330)	(0.057, 0.346)	(0.056, 0.336)
SN30	(0.064, 0.299)	(0.061, 0.330)	(0.048, 0.152)	(0.107, 0.194)	(0.061, 0.298)	(0.002, 0.016)	(0.056, 0.331)	(0.059, 0.348)	(0.058, 0.337)

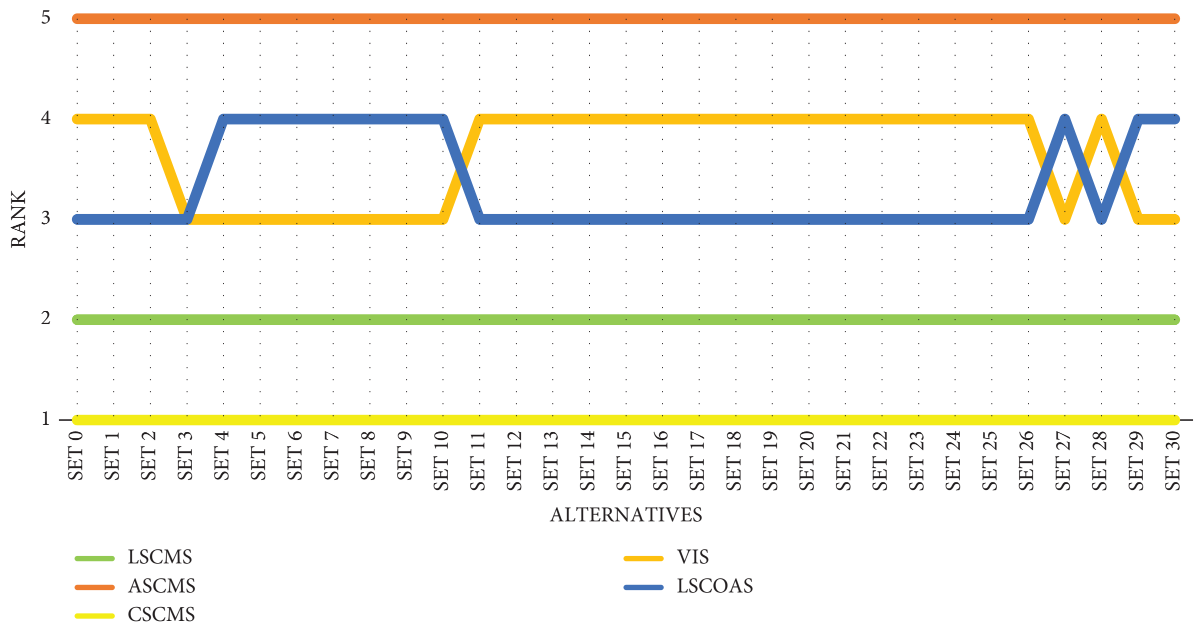

Figure 2: 30 new scenarios in a sensitivity analysis.

Table 10: The results of rough methods.

Strategies	Methods			
	Rough MARCOS	Rough WASPAS	Rough ARAS	Rough SAW
LSCMS	2	2	1	1
ASCMS	5	5	5	5
CSCMS	1	1	2	2
VIS	4	4	4	4
LSCOAS	3	3	3	3

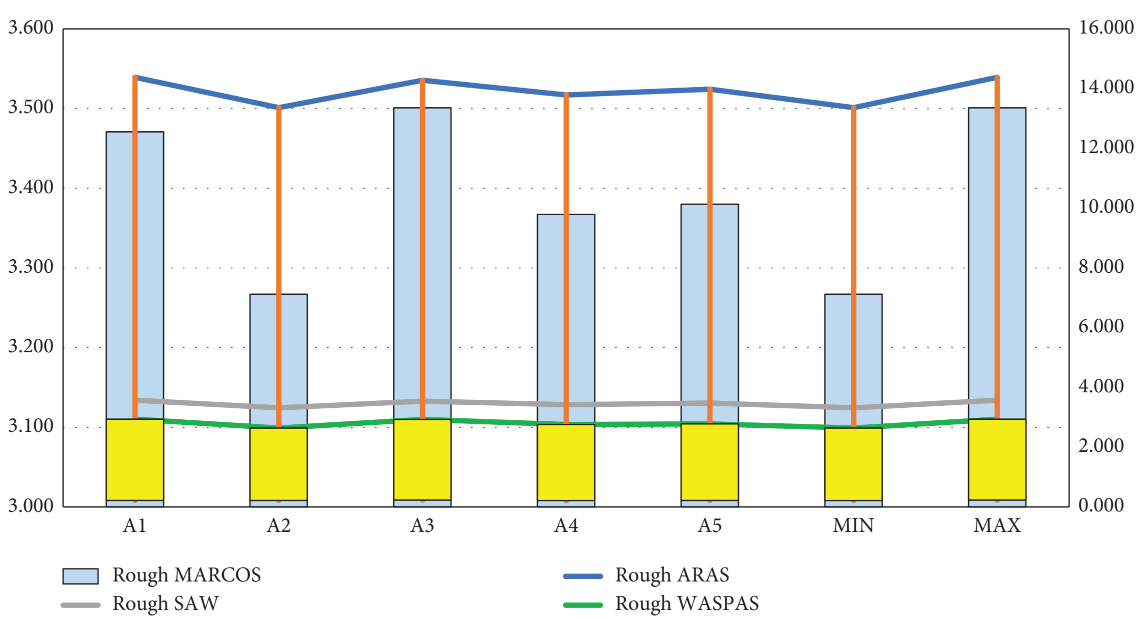

Figure 3: Alternative values in comparative analysis.

6. Conclusion and Suggestions

Companies develop and underline new strategies as alternatives for preventing SCM-related breakdowns during the COVID-19 pandemic because determining alternative supply scenarios and evaluating them with respect to operations has gained importance for coping with breakdowns in SCM during the pandemic process. With this perspective, it is aimed to analyse the factors leading to SCM breakdowns for manufacturing firms. In this study, a rough set-based SWARA-MARCOS methodology was used to prioritize factors leading to SCM breakdowns and to select the most successful SCM strategy in the COVID-19 process for food firms in the East Black Sea Region, respectively. Rough sets were preferred for aggregating the data of group decision making and thus data loss was prevented in this way. This was the advantageous side of rough sets compared with other methods. According to the results of the criteria weights calculated by using the rough SWARA method, the transportation capacity (TC) criterion was obtained as the most important leading to SCM breakdowns, and the local laws-related incentives (LLRI) criterion was found as the least important one. Other criteria ranking was LRMP > ASCF > BD > LRRPWTFM > ESW > SB > CFSMS, respectively.

It was determined that the most important weight was "transportation capacity (TC)." The result is consistent with the studies of Tao [57], Korucuk [58], and Gkiotsalitis and Cats [59] because with COVID-19, processes such as customs clearance level, delivery time, processing activities, especially the carrying capacity, have not been realized at the desired level. Depending on the carrying capacity, disruptions have occurred in production processes with the pandemic. In fact, the supply shock from the COVID-19 process has been impressive.

Another important factor is the "level of raw material procurement (LRMP)." The result is consistent with the studies of Askariazad and Wanous [60] and Xu et al. [61]. The supply level and level of raw materials are important in terms of realizing production levels at the desired level in the supply chain management, including the COVID-19 process.

Another important result reached in terms of supply chain management breaks in the COVID-19 process within the scope of the study is "alternative supplier capacity and flexibility (ASCF)." The obtained result supports the study of Kim and Zhao [62]. In this sense, determining the right suppliers to work with is of great importance in creating an effective supply chain because any negativity in the supply chain flow can make a difference in competition and can cause businesses to face some risks in the supply chain management [63].

Following that the most successful SCM strategy was determined as the collaborative supply chain management strategy (CSCMS) with the rough MARCOS method.

On the other hand, the best alternative in the results of the study was "collaborative supply chain management strategy (CSCMS)." This result supports the study of Maheshwari et al. [64] because this strategy is based on mutual cooperation and solidarity at different levels during the COVID-19 period, within the framework of bilateral principles or multilateral agreements, policies, procedures, plans, new activities, joint decision-making and participation, joint procurement practices, support for joint production, product/goods exchange, distribution management, supply chain management, joint transportation, new service arrangements and sharing, development of new procedures, and determination of appropriate costs, so it allows partnerships to be established between logistics sectors and businesses.

Firms having lean and agility capabilities mostly prefer CSCMS recently. This flexible strategy providing service quality and cost advantage has gained importance to carry out SCM functions for manufacturing firms during the pandemic process. The competitive power of firms is being supported by this strategy as similar to the literature.

In addition to its theoretical contributions, the study has very important implications for decision makers and practitioners in the food sector and those who are interested in the subject. These provide the opportunity to evaluate the factors of supply chain management breaks. It also pioneers a basic model for selecting the optimal alternative for supply chain management breaks and the supply chain strategy selection process. It provides a flexible and structured decision-making environment, that is, a decision-making environment and opportunity that considers different and separate views. Another valuable contribution of the study is that it helps decision makers make a new route in planning that considers the market conditions in the COVID-19 process in eliminating the disruptions in the supply chain by using the proposed model. In addition, the related study presents a new set of criteria suitable for real-worlddecision-making problems encountered in the food industry, addressing a critical area such as ensuring the efficiency of supply chain management in the COVID-19 process.

Finally, the evaluation of the supply chain management breakdown and the selection of the most ideal supply chain management strategy processes in the COVID-19 period, with the methods in the study, provided the opportunity to convey the practical approaches of the decision makers working in the food sector in a scientific perspective, and contributed to the interaction of theoretical and practical applications.

As opposed to that, the least successful SCM strategy was found as the agile supply chain management strategy (ASCMS). Other strategies were ranked as LSCMS > LSCOAS > VIS, respectively. A comparison analysis was executed with other methods (rough ARAS, WASPAS, and SAW) to underline the similarities and differences in terms of SCM strategies. The Spearman correlation coefficient was calculated between rough MARCOS and other methods and was found to be 0.9. As generally said, firms need to focus on alternative SCM strategies to evaluate their role in the operation for preventing breakdowns in supply chains because of the virus spreading in various regions. For future studies, criteria and strategies can be expanded and applied to different industries with hybrid methods. Also, comparison studies can be executed with respect to industry, region, country, and methodology.

In this study, some managerial implications for the food manufacturing industry were obtained. The aim of this study is to prioritize factors leading to SCM breakdowns and selecting the most successful SCM strategy in the COVID-19 process. According to the results of the rough SWARA method used in determining the weights of the factors in this study, the three most important factors are the following: transportation capacity, level of raw material procurement, and alternative supplier capacity and flexibility. According to these results, the managers of the companies should pay particular attention to the transportation capacity factor as much as possible. In addition, the managers of the companies need to keep the transportation capacity at the optimum level as possible. Besides, the managers of the companies should be careful about the level of raw material procurement and control their raw material stocks as much as possible. In addition, the managers of the companies are required to periodically check the capacity and flexibility of the company's alternative suppliers. This will prevent the companies from remaining without raw materials or semifinished products or products in both pandemic conditions and disaster situations. According to the results of the rough MARCOS method used in ranking the strategies, the best strategies are as follows: collaborative supply chain management strategy and lean supply chain management strategy. If the managers of the companies adopt the supply chain management in a collaborative way, they can cope with the pandemic conditions more easily. In addition, by using the lean supply chain management strategy as a support for the collaborative supply chain management strategy, the company's survival in pandemic and disaster conditions can be ensured. Although the effects of the COVID-19 pandemic have decreased, the results presented in this study will help the managers of the companies to choose the strategy they need to manage their companies against future possible pandemics.

Data Availability

The data used to support the findings of this study are included within this article. However, the reader may contact the corresponding author for more details on the data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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