Resilient Supplier Selection in Logistic 4.0: An integrated approach of Fuzzy Multi-Attribute Decision Making (F-MADM) and Multi-choice Goal Programming (MCGP) with Heterogeneous Information

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Abstract: Supplier selection problem has gained extensive attention in the prior studies. However, research based on Fuzzy Multi-Attribute Decision Making (F-MADM) approach in ranking resilient suppliers in logistic 4.0 is still in its infancy. Traditional MADM approach fails to address the resilient supplier selection problem in logistic 4.0 primarily because of the large amount of data concerning some attributes that are quantitative, yet difficult to process while making decisions. Besides, some qualitative attributes prevalent in logistic 4.0 entail imprecise perceptual or judgmental decision relevant information, and are substantially different than those considered in traditional supplier selection problems. This study, for the first time, develops a Decision Support System (DSS) that will help the decision maker to incorporate and process such imprecise heterogeneous data in a unified framework to rank a set of resilient suppliers in the logistic 4.0 environment. The proposed framework induces a triangular fuzzy number from large-scale temporal data using probability-possibility consistency principle. Large number of non-temporal data presented graphically are computed by extracting granular information that are imprecise in nature. Fuzzy linguistic variables are used to map the qualitative attributes. Finally, fuzzy based TOPSIS method is adopted to generate the ranking score of alternative suppliers. These ranking scores are used as input in a Multi-Choice Goal Programming (MCGP) model to determine optimal order allocation for respective suppliers. Finally, a sensitivity analysis assesses how the Supplier’s Cost versus Resilience Index (SCRI) changes when differential priorities are set for respective cost and resilience attributes.

Keyword: Logistic 4.0, Resilience, Supplier selection, Supplier’s Cost versus Resilience Index (SCRI), TOPSIS, Fuzzy Multi-Attribute Decision Making (F-MADM)

1. Introduction

With the increasing requirements for industrial process due to technological revolution, companies are facing rigorous challenges such as competitive global industry, increasing market unpredictability, swelling customized product demands and shortened product renewal cycle (Hofmann & Rüsch, 2017). Aligned
with the demanding industry, the fourth wave of technological innovation has been materialized, known as Industry 4.0. It refers to so-called fourth industrial revolution in discrete and process manufacturing, logistics and supply chain (Logistics 4.0), energy (Energy 4.0) etc., which is resulted due to the digital transformation of industrial markets (industrial transformation) integrated with smart manufacturing. Powered by foundational technology such as autonomous robots, simulation, cyber security, the cloud and additive manufacturing (Rüßmann et al., 2015), Industry 4.0 improves the manufacturing systems to an intelligent level that takes advantage of advanced information and manufacturing technologies to achieve flexible, smart, and reconfigurable manufacturing processes in order to address a dynamic and global market (Zhong, Xu, Klotz, & Newman, 2017).

As an essential and significant part of Industry 4.0, Logistics 4.0 concerns the various aspects of end-to-end logistics in the context of Industry 4.0, the Internet of Things (IoT), cyber-physical systems, automation, big data, cloud computing, and Information technology (Hofmann & Rüsch, 2017; i-SCOOP, 2017a; Rüßmann et al., 2015; Zhong et al., 2017). Logistics 4.0 aims to develop a smart logistics system to fulfill the customer requirements in the current connected, digitalized and rapidly changing global logistics market (i-SCOOP, 2017b). To adopt with an Industry 4.0 environment, extensive cutting-edge applications have been landed within Logistics 4.0. János Juhász and Tamás Bányai (Juhász & Bányai, 2018) identified challenges of just-in-sequence supply in the automotive industry from the aspect of Industry 4.0 solutions and detected impacts of Industry 4.0 paradigm on just-in-sequence supply. Ivanov et al. (Ivanov, Dolgui, Sokolov, Werner, & Ivanova, 2016) proposed a dynamic model and algorithm for short-term supply chain scheduling problem that simultaneously considered both machine structure selection and job assignments in smart factories. Brettel et al. (Brettel, Friederichsen, Keller, Rosenberg, & engineering, 2014) visualized the supply chain process by introducing cyber-physical systems to bridge the advanced communication between machines on the landscape of Industry 4.0.

With higher priority on customer satisfaction, incremental attention has been drawn to the availability, reliability, flexibility and agility of the logistics system (Barreto, Amaral, & Pereira, 2017; Witkowski, 2017). Unpredictable natural catastrophes or unexpected man-made disasters, such as earthquakes, floods, labor strikes and bankruptcy, would engender serious threat to the capability of the logistics system on these aspects. Despite of low occurrence probability, the tremendous financial impacts of the disruptions in any form on the logistics system are much more obvious. Renesas Electronics Corporation, a Japanese semiconductor manufacturer and the world’s largest manufacturer of microcontrollers is an industry 4.0 company. They launched the R-IN32M4-CL2 industrial Ethernet communication specific standard product (ASSP) with integrated Gigabit PHY to support the increasing network and productivity for Industry 4.0 companies on June 25, 2015 (Corporation, 2015). In earthquake and tsunami that struck the northeast coast of Japan on March 2011, the corporation’s Naka Factory and other manufacturing facilities were severely
damaged by the earthquake. The total losses caused by the disaster was 814.2 million USD, even though the insurance covered 198.9 million USD (Ye & Abe, 2012). UPS, the leading logistics company, which has achieved great advancement in the fields of digitalized logistics system and smart factory in the wave of Industry 4.0, suffers from the lack of resilient supply chain as well. During the hurricane Florence that threatened the east coast in mid-September 2018, the delivery rate reduced to 50% with thousands of delivery exceptions (SUPPLYCHAINDIVE, 2018).

To withstand against disruption a resilient supplier is indispensable in the sourcing decision process while operating under the principles of Logistics 4.0. A resilient supplier usually has high capability to resist or absorb disaster impact and can get back to usual performance quickly following a disaster (Y. Sheffi & Rice Jr, 2005; Y. J. M. P. B. Sheffi, 2005). To comprehensively evaluate the alternatives and select the optimal supplier, diverse factors are needed to be taken into consideration. Haldar et al. (Haldar, Ray, Banerjee, Ghosh, & Management, 2012, 2014) had defined the evaluation criteria in traditional resilient supplier selection problem, such as supply chain complexity, supplier resource flexibility, buffer capacity and responsiveness. Aiming to select the optimal resilient supplier in Logistics 4.0 environment, additional aspects are required to be taken into consideration regarding the features of Logistics 4.0.

In Logistics 4.0, most of the companies and related organizations are adopting end-to-end information sharing technologies because the amount of data produced and shared through the supply chain is significantly increasing (Domingo Galindo, 2016; G. Wang, Gunasekaran, Ngai, & Papadopoulos, 2016). Driven by the extensive, practical and efficient attributes, numerous applications of big data are employed in delivery forecasting, optimal routing, and productivity monitoring and labor reduction (Waller & Fawcett, 2013). Making well-informed decisions in sourcing process also involves a variety of massive data-based logistics aspects evaluation such as delivery lead time, inventory level, production capacity, and operation investment. Information sources such as ERP transaction data, GPS-enabled data, Machine-generated data and RFID data are frequently transferred, stored and retrieved through the logistics system, which require massive data manipulation methodology (Rozados & Tjahjono, 2014).

With the widespread use of IoT, cyber-physical systems, and Information technology, attention has been given on the supplier’s performance and ability in responding to changing customer demand with agility, warehouse automation, logistics system digitalization, information management and IT security, etc. The relevant data from these fields are generally collected in various format at quick velocity, and entails large volume—all-together leads to Big Data, which is often available as real-time and historical data. Data that are collected in real-time is characterized by time series whereas historical data is often presented in graphical format. Attributes that entail large amount of information in Logistics 4.0 are inventory level, schedule of delivery, production capacity, cost etc. Processing these large amounts of data requires a formal computation process that can enable decision maker to efficiently evaluate alternative decisions.
Therefore, for selecting resilient suppliers in Logistics 4.0, a decision-making framework is needed given the extensive impact of sourcing decision on the supply chain resiliency, efficiency and sustainability. The decision problem involves evaluation of several alternative suppliers against multiple conflicting criteria. Moreover, this problem even becomes more complicated when the decision relevant information (DRI) are in heterogeneous form such as qualitative information that are imprecise in nature and vague sometimes, and large number of quantitative information associated with the alternatives that are difficult to process. To address this problem, we propose a Decision Support System (DSS) leveraging the principle of Multi-Attribute Decision Making (MADM) to rank alternative suppliers from resilience and logistic 4.0 perspectives.

The key contributions of this study are:

i. As the existing research on MADM has limited applicability in the Logistics 4.0 environment, we, for the first time extend the F-MADM framework to Logistics 4.0 industries where selecting resilient suppliers has far reaching consequence. The proposed DSS is capable of handling qualitative attributes that entails imprecise DRI, and are substantially different than those considered in traditional supplier selection problem. Moreover, this DSS integrates large number of quantitative DRI, which in Logistics 4.0 environment is characterized by time series and graphical information. As such, we propose an integrated decision-making framework to process these heterogeneous information in a seamlessly unified framework to facilitate the resilient supplier selection process for a Logistics 4.0 industry.

ii. Commonly used fuzzy based TOPSIS technique solely depends on the standard triangular linguistic class to handle the qualitative appraisal in the decision making process and lacks the sophistication in processing the quantitative information. Our proposed DSS overcomes this limitation by successfully converting and integrating the crisp granular information extracted from graphically presented data into triangular fuzzy based TOPSIS decision matrix. Crisp granular or c-granular information refers to the pieces of information entailing well–defined crisp or ill-defined perceptual boundary consisting of sharp numbers (Ullah & Noor-E-Alam, 2018; Zadeh, 1997).

iii. Selecting suppliers considering all attributes that share equal preference usually generate inflated ranking score which is generic, however, sometimes fails to address the issue if a decision maker want to put more importance on one set of criteria than another. We divide the attributes in two set—mainly based on measure of resilience and cost—used as efficiency measure. We further demonstrate the capability of the proposed DSS to generate Supplier’s Cost versus Resilience Index (SCRI) based on customized preference given by the decision makers on those two set of attributes.

iv. We also extend the proposed DSS with the help of an order allocation model leveraging Multi-Choice Goal Programming (MCGP) technique. The optimal suppliers identified with the help of F-
MADM approach are only suitable for single-sourcing problems in which the procurement quantity can be satisfied by a single supplier. However, in a situation where procurement demand cannot be fulfilled by a single supplier, and strategic decision makers want to diversify their market, stabilize their sourcing channels while distributing risks on multiple suppliers and drive up competitiveness, allocating orders among competitive suppliers can turn out to be a viable strategy. As such, our framework will empower decision makers to allocate orders among alternative suppliers by taking into account the ranking of individual suppliers that has been generated via F-MADM approach.

The rest of this paper is organized as follows. In Section 2, we review the relevant literatures. Then in section 3 we present the theoretical concept needed to design the decision-making framework. Section 4 describe the proposed DSS for supplier evaluation and order allocation problem. In Section 5, we illustrate the effectiveness of the proposed DSS via a case study. Finally, in Section 6 we conclude the work conducted in this study with future research directions.

2. Literature review

MCDA approaches are widely adopted in the fields of transportation, immigration, education, investment, environment, energy, defense and healthcare (Devlin, Sussex, & Economics, 2011; Dodgson, Spackman, Pearman, & Phillips, 2009; Gregory et al., 2012; Mühlbacher, Kaczynski, & policy, 2016; Nutt, King, & Phillips, 2010; Wahlster, Goetghebeur, Kriza, Niederländer, & Kolominsky-Rabas, 2015). Howard and Ralph (Raiffa & Keeney, 1975) first introduce MCDA as a methodology for evaluating alternatives based on individual preference, often against conflicting criteria, and combining them into one single appraisal. Prior studies have also applied MCDA approach to select suppliers using multiple attributes (Lo & Liou, 2018; Ren, Xu, & Wang, 2018; Sodenkamp, Tavana, & Di Caprio, 2018). As one of the most prevalent MCDA approaches, Analytical Hierarchy Process (AHP) has been widely adopted to address supplier selection problems (De Felice, Deldoost, & Faizollahi, 2015; Prasad, Prasad, Rao, & Patro, 2016). Saaty (Saaty, 1980) firstly proposed the methodology of AHP, which was then refined by Golden et al (Golden, Wasil, Harker, & Studies, 1989). In AHP method, the feature of original data set is usually qualitative. In decision-making process, the master problem is decomposed to sub-problems, making the unidirectional hierarchical relationships between levels more understandable. Based on the subdivisions, pairwise comparison between alternatives are conducted to determine the importance of the criteria and priority over all alternatives. During this decision-making process, the evaluation of alternatives could be extended to qualitative field while multiple criteria are considered, and the consistency of the system are satisfied. However, due to the subjectivity of the qualitative information resulted from the discrepancy of decision makers on experience, knowledge and judgment, the uncertainty and imprecise nature in the data are not dealt with, which may impair the reliability and robustness of the result.
To help the stakeholders establish a more accurate and reliable approach, Yoon (Yoon, 1987) and Hwang et al. (Hwang, Lai, & Liu, 1993) developed TOPSIS (Technique for order preference by similarity to an ideal solution). The underlying idea is that the optimal solution should have the closest distance from the Positive Ideal Solution (PIS) and longest distance from the Negative Ideal Solution (NIS). TOPSIS can handle quantitative input data, which is different from the basic feature of AHP. Because of its precise nature, TOPSIS has been broadly applied in supplier selection problem. Shahrroudi and Tonekaboni (Shahroudi & Tonekaboni, 2012) adopted TOPSIS in the supplier selection process in Iran Auto Supply Chain, in which both the numerical and linguistic evaluation criteria are considered to determine the preferential alternatives. In this study, numerical numbers (without consideration of fuzziness of data set) are assigned to qualitative data directly to generate the quantitative decision matrix for TOPSIS. To develop an integrated decision-making framework, some group of researchers aggregated AHP with TOPSIS to better evaluate the alternative suppliers (Bhutia & Phipon, 2012; Şahin & Yiğider, 2014a). However, most of these methods utilized crisp information, and thus uncertainty, impreciseness and fuzziness nature of the judgmental information are not considered.

To obtain better results in problems wherein decision making and analysis are significantly affected by the uncertainty inherent in decision relevant information, the fuzzy technique was introduced. Atanassov (K. T. Atanassov, 1986), at first defined the concept and properties of Intuitionistic fuzzy set, which was then adopted by Haldar et al. and Boran et al. (Boran, Genç, Kurt, & Akay, 2009; Haldar, Ray, Banerjee, & Ghosh, 2014) to the aggregated decision-making framework in supplier selection problem. Wang et al. (Haibin, Smarandache, Zhang, & Sunderraman, 2010; H. Wang, Smarandache, Sunderraman, & Zhang, 2005) proposed the concept of single valued neutrosophic set (SVNS), which can characterize the indeterminacy of a perceptual information more explicitly. SVNS was then aggregated with TOPSIS by Sahin and Yiğider (Şahin & Yiğider, 2014b) to replace the crisp information in the decision matrix. Their findings show that TOPSIS when integrated with SVNS performs better with incomplete, undetermined and inconsistent information in MCDA problems. As most of the membership functions in the researches mentioned above are assumed to be triangular, to find another way to capture the vagueness of the qualitative information, Positive Trapezoidal Fuzzy Number (PTFN) was proposed by Kaufman and Gupta (Bohlender, Kaufmann, & Gupta, 1986) and was introduced by Herrera (Herrera & Herrera-Viedma, 2000) in group decision making problems. Chen et al (C.-T. Chen, Lin, & Huang, 2006) adopted PTFN to present a fuzzy decision-making framework to deal with supplier selection problem.

Because providing opinion as a number in interval [0,1] does not reflect the uncertainty in expert’s judgmental information, it is more suitable to represent this degree of certainty by an interval. Wang and Li (Guijun & Xiaoping, 1998) defined the concept of Interval-valued Fuzzy Sets (IVFS) and Ashtiani et al. (Ashtiani, Haghhighrad, Makui, & ali Montazer, 2009) extend the application of IVFS in TOPSIS to solve
Multi Criteria Decision Making problems. Additionally, Atanassov and Gargov (K. Atanassov & Gargov, 1989) proposed the notion of Interval-valued Intuitionistic Fuzzy Sets (IVIFS) as a further generalization of fuzzy set theory. Nayagam et al. (Lakshmana Gomathi Nayagam, Muralikrishnan, & Sivaraman, 2011) adopted IVIFS in the ranking problem of multi criteria decision making. The method was then extended by Chen et al. (T.-Y. Chen, 2015; T.-Y. Chen, Wang, & Lu, 2011) to multi decision makers perspective, while Izadikhah (Mohammad, 2012) implemented the approach in supplier selection problem. After reviewing the relevant literatures, we found that the state-of-the-art studies deals with only qualitative attributes, while many of the essential and significant evaluation criteria may entail quantitative decision relevant information, especially for the resilient supplier selection problem under the principle of Logistics 4.0. It is true that the existing research have shown promising potential of MCDA methods and fuzzy techniques in supplier selection problems (Hasan, Shohag, Azeem, Paul, & Management, 2015; Jiang, Faiz, & Hassan, 2018). However, there are limitations of the state-of-the-art literatures: (i) to the best of our knowledge, no existing research extends F-MADM framework in supplier evaluation problems leveraging large number of information (time series and graphical information), (ii) no prior study investigated F-MADM approach for evaluating suppliers’ performance from resilience and Logistics 4.0 perspective, simultaneously, and (iii) it is not clear how fuzzy based TOPSIS can be extended to process inherent uncertainty in decision relevant information associated with both the quantitative and qualitative attributes. These gap in the existing studies creates an avenue for further research to extend F-MADM framework to help decision makers in Logistics 4.0 industries strategically select resilient suppliers considering qualitative and large number of quantitative information, which lies in the central focus of this study.

3. MADM and fuzzy logic

3.1 MADM

Multi Attribute Decision Making (MADM) provides a comprehensive decision analysis framework that could help the stakeholders balance the advantages and disadvantages of the alternatives in a multi-dimensional optimization problem, in which alternatives and evaluation attributes are the essential variables. The general decision-analysis procedure of MADM and the corresponding steps are summarized as follows (Thokala et al., 2016):

| Step 1 | Defining the decision problem | Select optimal supplier with highest resilience over a group of alternative suppliers |
| --- | --- | --- |
| Step 2 | Selecting and structuring attributes | Identify the evaluation attributes with respect to supplier resilience |
| Step 3 | Measuring performance | Gather data about the alternatives’ performance on the attributes and summarize this in a decision matrix |
|-------|-----------------------|--------------------------------------------------------------------------------------------------|
| Step 4 | Scoring alternatives  | Evaluate the performance of the alternative suppliers based on the objective of the attributes |
| Step 5 | Weighting criteria and decision makers | Determine the weight of attributes and decision makers based on their importance |
| Step 6 | Calculating aggregate scores | Use the alternatives’ scores on the attributes and the weights for the attributes and decision makers to get “total value” by which the alternatives are ranked with TOPSIS |
| Step 7 | Dealing with uncertainty | Perform Sensitivity analysis to understand the level of robustness of the MADM results |
| Step 8 | Reporting and examination of findings | Interpret the MADM outputs, including sensitivity analysis, to support decision making |

### 3.2 Technique for order preference by similarity to an ideal solution (TOPSIS)

TOPSIS is a decision-making technique wherein the alternatives are evaluated based on their numerical distance to the ideal solution. The closer the distance of an alternative to the ideal solution and the father to the negative ideal solution, the higher a grade it would obtain. In our research, because we are adopting Triangular Fuzzy Number (TFN) to express the performance of the alternatives, Euclidian Distance is used to measure the performance of the alternatives, and the function is described as below (Şahin & Yiğider, 2014a):

\[
s^+_i = \sqrt{\sum_{j=1}^{n} \left( (a_{ij} - a^+_j)^2 + (b_{ij} - b^+_j)^2 + (c_{ij} - c^+_j)^2 \right) } \quad i = 1, 2, \ldots, n
\]

\[
s^-_i = \sqrt{\sum_{j=1}^{n} \left( (a_{ij} - a^-_j)^2 + (b_{ij} - b^-_j)^2 + (c_{ij} - c^-_j)^2 \right) } \quad i = 1, 2, \ldots, n
\]

\[
\tilde{\rho}_j = \frac{s^-}{s^+ + s^-}, \quad 0 \leq \tilde{\rho}_j \leq 1
\]

Where \(s^+_i\) and \(s^-_i\) are the positive and negative ideal solution respectively, \(\tilde{\rho}_j\) is the closeness coefficient (CC), \(a_{ij}, b_{ij}, c_{ij}\) are the component of the TFN that expressing the performance of alternatives on criteria \(j\), \(a^+_j, b^+_j, c^+_j\) are the corresponding components of the Positive Ideal Solution (PIS) and \(a^-_j, b^-_j, c^-_j\) are the corresponding components of Negative Ideal Solution (NIS).
3.3 Properties of Triangular Fuzzy Number (TFN)

Triangular Fuzzy Number (TFN) is a fuzzy number represented with three points as follows:

\[ \tilde{A} = (a, b, c) \]

Where \([a, c]\) is the support and \(\mu_{\tilde{A}}(b) = 1\) is the core of the fuzzy number. This representation is interpreted in terms of membership functions as follows:

\[ \mu_{\tilde{A}}(x) = \begin{cases} 
0, & \text{for } x < a \\
\frac{x-a}{b-a}, & \text{for } a < x < b \\
\frac{c-x}{c-b}, & \text{for } b < x < c \\
0, & \text{for } c < x 
\end{cases} \]  

(3.4)

Figure 1. Triangular Fuzzy Number

The operation of the TFN could be summarized as follows (Mahapatra, Mahapatra, & Roy, 2016): let \(A = (a_1, b_1, c_1), B = (a_2, b_2, c_2), r\) is a real number, then,

1) Addition: \(A + B = (a_1 + a_2, b_1 + b_2, c_1 + c_2)\)

2) Subtraction: \(A - B = (a_1 - c_2, b_1 - b_2, c_1 - a_2)\)  

3) Multiplication: \(A \times B = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2)\)

\[ A \times r = (a_1 \times r, b_1 \times r, c_1 \times r) \]  

(3.5)

The underlying reason for using TFN instead of other fuzzy techniques is primarily due to the probability-possibility consistency principle that induces TFN from time series data. Moreover, TFN also provides the basis for converting granular information that are extracted from graphically presented historical data.

3.4 Membership function and reliability modification

The definition of membership function was first introduced by Zadeh (Şahin & Yiğider, 2014a), where the membership functions were used to operate on the domain of all possible values. In fuzzy logic, membership degree represents the truth value of a certain proposition.

Different from the concept of probability, truth value represents membership in vaguely defined sets. For any set \(X\), the membership degree of an element \(x\) of \(X\) in fuzzy set \(A\) is denoted as \(\mu_A(x)\), which quantifies
the grade of membership of the element \( x \) to the fuzzy set \( A \). To calculate the membership degree, the universe of discourse concerning different attributes are fuzzified using linguistic classes according to the granule definiteness axiom of multi-granularity (A.M.M. Sharif Ullah, 2005; Ullah, 2005). Figure 2 shows the fuzzification of universe of discourse or frame of discernment consisting \([a, b]\).

For the frame of discernment shown in the figure above, the membership functions for the 7 different classes (B, MB, ..., VVG) are calculated as follows:

\[
m_B = \max \left( 0, \frac{a_3 - x}{a_3 - a} \right)
\]

\[
m_{MB} = \max \left( 0, \min \left( \frac{x - a_1}{a_3 - a_1}, \frac{a_5 - x}{a_5 - a_3} \right) \right)
\]

\[
\ldots \ldots
\]

\[
m_{VVG} = \max \left( 0, \frac{x - a_{11}}{b - a_{11}} \right)
\]

where \( a_i = a + \frac{b-a}{2 \times 7}, \quad i = 1, 2, ..., (2 \times 7 - 1) \), and 7 is the number of class in this frame of discernment.

The membership functions are assumed to be triangular and symmetric. The membership function for each class depends on the frame of discernment of the attribute.

As the membership functions are assumed triangular and symmetric for the fuzzified frame of discernment, the uncertainty and impreciseness of the functions need to be taken into consideration. Jiang et al (Wen, Miaoyan, & Chunhe, 2017) proposed a reliability-based modification to deal with uncertainty of information and the reliability of information sources. The reliability of the membership functions is measured by the static reliability index and dynamic reliability index. Static reliability index is defined by the similarity among classes, while dynamic reliability index is measured by the risk distance between the test samples and the overlapping area among classes, respectively. The comprehensive reliability is computed by the product of the two index and the reliability-based membership function are fused using Dempster’s combination rule (Dempster, 1967; Wen et al., 2017). The numerical examples provided by Jiang et al. verified the effectiveness of the reliability modification approach in membership functions.

The static reliability index is measured by the overlapped area between two adjacent classes. In Figure 3, the shaded area is the overlapped region between classes M and MG.
The larger the overlapped area between classes M and MG, the more likely that an input data is wrongly recognized in a linguistic class. The similarity between classes M and MG $sim_{M, MG}$ in a certain attribute and the corresponding static reliability index $R_j^s$ for $C_j$ can be described as (Wen et al., 2017):

$$sim_{M, MG} = \frac{\int_{c}^{d} \min (m_M(x), m_{MG}(x)) \, dx}{\int m_M(x) + m_{MG}(x) - \int_{c}^{d} \min (m_M(x), m_{MG}(x)) \, dx}$$  \hspace{1cm} (3.7)$$

$$R_j^s = \sum_{i<t} (1 - sim_{it})$$  \hspace{1cm} (3.8)$$

; where $i$ and $l$ are the adjacent classes in the same universe of discourse in one attribute.

The dynamic reliability index is measured with a set of test sample and calculated by the risk distance between the peak of overlap area and the test value.

$$d_{M, MG} = \frac{|T_j - P_{M, MG}|}{D}$$  \hspace{1cm} (3.9)$$

$$R_j^d = e^{\sum_{l=1}^{2} d(l-1)i}$$  \hspace{1cm} (3.10)$$

; where $D$ is the range of the universe of discourse of $C_j$, which is $(a - b)$ in Figure 3.

Then the comprehensive reliability index for $C_j$ can be defined as:

$$R_j = R_j^s \times R_j^d$$  \hspace{1cm} (3.11)$$

After the normalization we get,
Then, the reliability-modified membership degree can be calculated as:

\[ m_{ji}^{R_j} = R_j^* \times m_l \]  

(3.13)

where \( l \) is a linguistic class in a universe of discourse.

4. Quantitative data analytics

4.1 Processing time-series data

Ullah and Shamsuzzaman (A. M. M. Sharif Ullah & Shamsuzzaman, 2013) proposed an approach that can represent the uncertainty under a large set of continuous time-series input parameters (temporal data) by point cloud and transfer it to a graphical fuzzy number based on probability-possibility transformation. The transformation process is generalized as follows:

Assume, we have a temporal data presented in time-series data as shown in Figure 5.

If we set the \( x(t) \) as the x-coordinate and \( x(t+1) \) as the y-coordinate, this set of parameters could be represented as a point cloud as shown in Figure 6, providing a visual/computational representation of variability, modality, and ranges associated with the quantity.

Assume, \( g(x) \) be the probability density functions (pdf) that represent the underlying point-cloud of \( x(t) \), the cumulative pdf, \( F(x) \), can be defined as:

\[ F(x) = \int g(x)dx \]
Let \( PrA(x) \) denote the following formulation:

\[
PrA(x) = \frac{dF(x)}{dx}
\]

A possibility distribution given by the membership function \( \mu(x) \) can be defined as:

\[
\mu(x) = \frac{PrA(x)}{\max(PrA(x) \mid \forall x \in X)}
\]

![Graphical Triangular Fuzzy Number](image.png)

Figure 7. Graphical Triangular Fuzzy Number.

After the probability-possibility transformation, the point cloud is transferred to a triangular fuzzy number in a graphical format as shown in Figure 7. In what follows, the triangular fuzzy set can be expressed as:

\[
A = (425, 442, 452)
\]

### 4.2 Processing graphical information

In the Logistics 4.0 system, the data are not always generated in the format of continuous time-series. Sometimes they are generated discretely and stored in the database for future access. These historically stored data can be expressed in pieces of graphs (Domingo Galindo, 2016) because when visualized, these pieces of graphs can potentially present a large amount of information in an easy-to-understand way. Then, the necessary DRI in terms of pieces of crisp granular information can be extracted from these graphically presented data according to (Ullah & Noor-E-Alam, 2018). Figure 8(a) shows the visualization of data collected for five suppliers concerning cost per unit of product and production capacity. Then, graphical data associated with a single supplier can be extracted from the combined graph and is presented in Figure
8(b). Once data for individual supplier is presented graphically, then the associated DRI concerning cost per unit of product and production capacity can be extracted in the form of crisp granular information or ranges as visualized in Figure 8(c) and Figure 8(d), respectively.

![Figure 8](image)

**Figure 8.** Graphical information extraction process.

### 5.0 Proposed supplier evaluation and order allocation model

In this Supplier Evaluation and Order Allocation Model, both the quantitative and qualitative information are characterized by Triangular Fuzzy Number (TFN) to evaluate the performance of the alternatives in a unified platform, simultaneously. For the quantitative attributes, time-series and non-time series data are
transferred to fuzzy set through point cloud and graphic extraction approaches, respectively, while qualitative assessments, including performance and weight appraisal, are transferred directly based on the standard fuzzification process of the frame of discernment. With the fuzzy set for all attributes and weights, the weighted decision matrix is constructed. Then the algorithm of TOPSIS is performed to evaluate the performance of the alternatives and generate the list of preference based on the obtained ranking score. Finally, the ranking score are regarded as the coefficient in the MCGP to calculate the order allocation plan that best fulfill the requirements of the decision makers. To provide a comprehensive and understandable illustration for the proposed supplier evaluation and order allocation model, we present a complete computation process with detailed description below:

**Step 1: Transfer the time-series data to TFN**

At first, the time-series data, for supplier $S_i$ on attribute $C_j$ consists are expressed by a point cloud entailing $P(x(t), x(t + 1))$ according to the principle explained in section 4.2. After the point cloud transformation, the data are transferred to a TFN as shown in Figure 4.2, which can be represented by a TFN in the form of $A_{ij} (a_{ij}, b_{ij}, c_{ij})$.

**Step 2: Transfer non-temporal graphical data to TFN**

After the information extracted from the graphical information, the randomly obtained $r$ number of crisp granular information or ranges for supplier $S_i$ on attribute $C_j$, $R_{ijr}(p_{ijr}, q_{ijr})$, are presented in Table 2.

| Ranges  | $C_i$  |
|---------|--------|
| $R_{ijr}$ ($p_{ijr}, q_{ijr}$) |        |

After we collected all the crisp granular information for every alternative supplier, we fuzzify the frame of discernment associated with every non-time-series attribute $C_j$ based on the fuzzification approach proposed in (Ullah & Noor-E-Alam, 2018). In the fuzzification process, the span of the frame of
discernment is generated by the minimum and maximum of all the extracted crisp granular information for a certain attribute regarding all the alternative suppliers, while the number of classes is determined according to the granule definiteness axiom (A.M.M. Sharif Ullah, 2005; Ullah, 2005). For Example, if \( p_{\min} = \min_r p_{ijr} \), \( q_{\max} = \max_r q_{ijr} \), the frame of discernment of \( C_j \) can be fuzzified as follows:

After the fuzzification process, the linguistic classes \( l \) and associated TFN table are constructed as in Table 3:

| Linguistic Terms | TFN \((a, b, c)\) |
|------------------|------------------|
| \( B \)          | \( a_B \)        | \( b_B \) | \( c_B \) |
| \( MB \)         | \( a_{MB} \)     | \( b_{MB} \) | \( c_{MB} \) |
| \( \ldots \)     | \( \ldots \)     | \( \ldots \) | \( \ldots \) |
| \( l_m \)        | \( a_{l_m} \)    | \( b_{l_m} \) | \( c_{l_m} \) |

Where \( m \) is the number of linguistic classes and \( l_m \) is \( m^{th} \) linguistic class.

With the fuzzified frame of discernment, the membership degree for every range value \( R_{ijr}(p_{ijr}, q_{ijr}) \) on each linguistic class is computed based on (3.6).

\[
m_{ij} = \frac{\int_{x \in R} m_F(x)dx}{\|R\|}
\]

where \( R \) refers to the span of the criteria and \( \|R\| \) refers to the largest segment of \( R \) that belongs to the support \( m_F \). This way, the membership degree of \( R_{ijr}(p_{ijr}, q_{ijr}) \) on \( C_j \) at linguistic class \( l \) is calculated as \( M_{ijrl} \).

Because all the membership functions are assumed to be symmetric and triangular, we perform reliability modification for the calculated membership degrees. According to equations (3.7-3.12), the comprehensive reliability indexes for \( C_j \) could be generated as \( R_{C_j} \). Multiplied with the obtained \( R_{C_j} \) based on (3.13), the original membership degree \( M_{ijrl} \) can be modified as \( M'_{ijrl} \). As there are \( r \) computed modified membership degrees for each linguistic class, we aggregate them as follows:

\[
M'_{ijrl} = \sum_r M'_{ijr}
\]

Then, the reliability modified membership degrees are normalized to induce TFN for the integrated TOPSIS decision matrix as mentioned below:

\[
N_{ijl} = \frac{M'_{ijl}}{\sum M'_{ijl}}, \sum N_{ijl} = 1
\]
To generate the TFN for the attribute involving non-time series graphical information, we utilized the TFN for every linguistic class in Table 3 and the membership degrees calculated above. In this integration process, without loss of information generalizability, the membership degree is regarded as the weight of each linguistic class for every alternative concerning each attribute. Then the membership degree is converted to TFN that will be used in the TFN based TOPSIS decision matrix. The integrated TFN is presented as $A_{ij} (a_{ij}, b_{ij}, c_{ij})$:

$$a_{ij} = \sum_l a_l N_{ijl}$$
$$b_{ij} = \sum_l b_l N_{ijl}$$
$$c_{ij} = \sum_l c_l N_{ijl}$$

(5.4)

Where $l$ is the linguistic class in Table 3.

**Step 3: Transfer the linguistic data to Triangular Fuzzy Sets**

The qualitative assessments given by the decision makers for each supplier against each attribute are directly transferred to respective TFNs. For example, a set of qualitative assessments for $i^{th}$ suppliers on attribute $C_j$ given by $k^{th}$ decision makers (DM) can be represented as in Table 4:

| Supplier/DMs | $DM_1$ | $DM_2$ | ... | $DM_k$ |
|--------------|--------|--------|-----|--------|
| $S_1$        | $L_{1j1}$ | $L_{1j2}$ | ... | $L_{1jk}$ |
| $S_2$        | $L_{2j1}$ | $L_{2j2}$ | ... | $L_{2jk}$ |
| ...          | ...    | ...    | ... | ...    |
| $S_i$        | $L_{ij1}$ | $L_{ij2}$ | ... | $L_{ijk}$ |

These qualitative appraisals are then converted to respective TFNs as presented in Table 5:

| Supplier/DMs | $DM_1$ | $DM_2$ | ... | $DM_k$ |
|--------------|--------|--------|-----|--------|
| $S_1$        | $(a_{1j1}, b_{1j1}, c_{1j1})$ | $(a_{1j2}, b_{1j2}, c_{1j2})$ | ... | $(a_{1jk}, b_{1jk}, c_{1jk})$ |
| $S_2$        | $(a_{2j1}, b_{2j1}, c_{2j1})$ | $(a_{2j2}, b_{2j2}, c_{2j2})$ | ... | $(a_{2jk}, b_{2jk}, c_{2jk})$ |
| ...          | ...    | ...    | ... | ...    |
| $S_i$        | $(a_{ij1}, b_{ij1}, c_{ij1})$ | $(a_{ij2}, b_{ij2}, c_{ij2})$ | ... | $(a_{ijk}, b_{ijk}, c_{ijk})$ |
Finally, the TFN-based TOPSIS decision matrix is constructed by incorporating and aggregating the conflicting qualitative assessments provided by all the DMs involved in the decision-making process. This is similar to what is proposed in (C.-T. Chen et al., 2006) as follows:

\[ A_{ij} (a_{ij}, b_{ij}, c_{ij}) = (\min_k a_{ijk}, \frac{\sum_k b_{ijk}}{k}, \max_k c_{ijk}) \]  

(5.5)

**Step 4: Calculate the weight for criteria**

The weight of all the criteria is determined by the DMs on the basis of linguistic assessment as well. In the same way, we fuzzified the frame of discernment of the criteria weight as shown in Table 6 and Figure 10:

| Weight of Criteria       | TFN (a, b, c) |
|--------------------------|--------------|
| Linguistic Terms         |   VUI        |
|                          |   (0,0,1,0,2) |
|                          |   UI         |
|                          |   (0,1,0,2,0,3) |
|                          |   ...        |
|                          |   EI         |
|                          |   (0,8,0,9,1) |

Then the weight of each criteria \(w_j(a_j, b_j, c_j)\) is computed according to step 3.

**Step 5: Conduct TOPSIS to generate the ranking score for suppliers**

Because in the weighted decision matrix, the TFNs concerning each supplier against each attribute have diverse support defined as \([a_{ij}, c_{ij}]\), we first normalized the TFN \(A_{ij} (a_{ij}, b_{ij}, c_{ij})\) on all criteria before performing TOPSIS based on (C.-T. Chen et al., 2006):
\[
A'_{ij}(a'_{ij}, b'_{ij}, c'_{ij}) = \left( \frac{a_{ij}}{\max c_{ij}'}, \frac{b_{ij}}{\max c_{ij}'}, \frac{c_{ij}}{\max c_{ij}'} \right), \forall j \in G_1 
\]

\[
A'_{ij}(a'_{ij}, b'_{ij}, c'_{ij}) = \left( \frac{\min a_{ij}}{c_{ij}'}, \frac{\min a_{ij}}{b_{ij}'}, \frac{\min a_{ij}}{a_{ij}'} \right), \forall j \in G_2
\]

where \( G_1 \) is the set of beneficial attributes which are to be maximized and \( G_2 \) is the set of non-beneficial attributes which are to be minimized.

As now we have the normalized TFN \( A'_{ij}(a'_{ij}, b'_{ij}, c'_{ij}) \) for all suppliers \( S_i \) on every attribute \( C_j \) and the criteria weight \( w_j(a_j, b_j, c_j) \), the normalized and weighted TFN based TOPSIS decision matrix \( \{A'_i\} \) is constructed based on (3.5):

\[
A'_{ij}(a'_{ij}, b'_{ij}, c'_{ij}) = A'_{ij} \times w_j
\]

The Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are determined as (C.-T. Chen et al., 2006):

\[
A_{pj}(a_{pj}, b_{pj}, c_{pj}) = \max_i c_{ij}^*
\]

\[
A_{nj}(a_{nj}, b_{nj}, c_{nj}) = \min_i a_{ij}^*
\]

And, finally the CC for \( S_i \) is generated as:

\[
d_i^+ = \sqrt{\frac{\sum_j (a_{ij} - a_{pj})^2 + \sum_j (b_{ij} - b_{pj})^2 + \sum_j (c_{ij} - c_{pj})^2}{3}}
\]

\[
d_i^- = \sqrt{\frac{\sum_j (a_{ij} - a_{nj})^2 + \sum_j (b_{ij} - b_{nj})^2 + \sum_j (c_{ij} - c_{nj})^2}{3}}
\]

\[CC = \frac{d_i^-}{d_i^- + d_i^+}\]

The higher the CC, the higher will be the ranking for a particular supplier. Ranking is given as an ascending order starting from 1 for a supplier with highest CC, and follows chronological order for rest of the suppliers.

**Step 6: Integrate MCGP with F-MADM to determine optimal order allocation policy**

It is perhaps not surprising that a single supplier may not always have the ability to supply the entire ordered quantity. In addition, strategic decision makers may opt for diversifying the sourcing channels while ensuring stability and competitiveness among alternative suppliers. These altogether make it feasible that decision makers often times have to depend on multiple suppliers, requiring an optimal order allocation strategy that takes into account the supplier preferential ranking \( R_i \) generated via F-MADM approach as input. Multi-choice Goal Programming (MCGP)—a viable approach in this regard—can successfully be
integrated with F-MADM based DSS to devise an optimal order allocation plan (Liao & Kao, 2011). MCGP has the potential to address multi-attribute decision making problems, wherein decision makers aim to minimize the penalty of a set of objectives assigned to all attributes. The essential idea of integrating F-MADM approach with MCGP is to enable such an optimal order allocation policy that can maximize the total value created from the intended procurement plan. The Total Value of Procurement (TVP) is quantitatively defined as the aspiration level that is set by the decision makers, and it can be sometimes conservative based on the company’s resource limitations and incompleteness of available information. A well-judged and/or conservative aspiration level e.g. TVP can avoid the potential negative effect of the intended procurement plan. Often times, in MCGP setting, the decision makers are allowed to set a multi-choice aspiration level (MCAL) for each goal to help avoid unintended underestimation and overestimation of decision making. (Chang, 2008). The MCAL for each target associated with multiple attributes is presented in certain interval values, allowing the decision makers to consider uncertainty/incompleteness of available decision relevant information. Therefore, once the closeness coefficients for each alternative suppliers are generated at the end of Step 6, these are used as the coefficient in the proposed MCGP according to (Guneri, Yucel, & Ayyildiz, 2009) so that the TVP is maximized.

Leveraging this principle, we formulated the MCGP as follows:

\[
\text{Minimize } \sum_i (d_i^+ + d_i^-) + \sum_j (e_j^+ + e_j^-), \quad i = 1, 2, 3, 4, j = 1, 2, 3
\]

\[\text{Subject to:}\]

\[
\sum_{n=1}^{n} C_n \times x_n - d_1^+ + d_1^- \geq T \tag{1}
\]

\[
\sum_{n=1}^{n} U_n \times x_n - d_2^+ + d_2^- = y_1 \tag{2}
\]

\[
y_1 - e_1^+ + e_1^- = l_{min} \tag{3}
\]

\[
l_{min} \leq y_1 \leq l_{max} \tag{4}
\]

\[
\frac{(\sum_{n=1}^{n} L_n \times x_n)}{\sum_{n=1}^{n} x_n - d_3^+ + d_3^-} = y_2 \tag{5}
\]

\[
y_2 - e_2^+ + e_2^- = r_{min} \tag{6}
\]

\[
r_{min} \leq y_2 \leq r_{max} \tag{7}
\]

\[
\sum_{n=1}^{n} x_n - d_4^+ + d_4^- \leq Q \tag{8}
\]

\[
x_n, d_i^+, d_i^-, e_j^+, e_j^- \geq 0 \tag{9}
\]
Where:

\[ d_i^+, d_i^-, e_m^+, e_m^- \] stand for the penalties in violation of respective constraints
\[ x_n \] is the optimal ordered quantity assigned to \( n \)th Supplier
\[ C_n \] is the closeness coefficients (CC) of the available suppliers
\[ T \] is the total value created from procurement (TVP)
\[ U_n \] is the unit cost of quantity when purchased from \( n \)th supplier
\[ y_1 \] is the total available budget for the procurement
\[ I_{min}, I_{max} \] are the lower limit and upper limit on the budget, respectively
\[ L_n \] is lead time of the \( n \)th supplier
\[ y_2 \] is the total allowable lead time for a particular order
\[ R_{min}, R_{max} \] are the lower limit and upper limit on lead time, respectively
\[ Q \] is the procurement level set by the decision makers
\[ n \] is the number of alternative suppliers

The objective function aims to minimize the total non-achievement penalties of multiple targets assigned in different constraints. Constraint (1) ensures that the orders should be allocated among multiple suppliers considering their preferential ranking in such a way so that TVP is maximized. Meanwhile, constraint (2) refers to the goal of procurement budget, signifying that total procurement cost will not exceed the budget after including the positive and negative deviation of the intended goal. Constraints (3) and (4) explains the aspiration levels of the goal associated with procurement budget. In a similarly way, constraint (5), (6) and (7) illustrate the lead time preference along with the aspiration levels associated with corresponding lead times. Finally, constraint (8) with consideration of deviations from the procurement level goal, restrict that the total order allocated to multiple suppliers must equal the procurement level set by the decision makers.

Such an MCGP model is anticipated to handle multiple objectives as a decision maker seeks the optimal solution from a set of feasible solutions considering the aspiration levels of the objectives; thus, enabling the management to optimally balance their requirements among alternative suppliers when the multiple requirements cannot be satisfied by a single supplier.

The proposed decision-making framework is presented as a flow chart in Figure 11:
6. Case illustration

To demonstrate the effectiveness and usefulness of the proposed supplier evaluation and order allocation DSS, we present a hypothetical case study that is generalizable to companies operating under logistics 4.0.
Such logistic 4.0 companies concern different aspects of end-to-end logistics and supply chain management, which transforms the way those companies manage their logistics operations. This transformation is powered by the digitalization of supply chain system—characterized by the speed, flexibility, real-time connectedness among different entities of logistics 4.0—arguably, supply chain 4.0. Crucially, effective sourcing of raw materials plays a significant role in achieving that desired level of efficiency, responsiveness and resilience in the context of connected, decentralized and digitalized supply chain. Often times, a set of alternative suppliers may serve the purpose of providing a particular raw material. Strategic decision makers responsible for taking such high-impact sourcing decisions must choose a supplier among available alternatives who can best serve the requirement of resilience, sustainability and efficiency. Therefore, the supplier evaluation and selection process in this context of logistics 4.0 is characterized as a decision-making problem comprising multiple conflicting attributes. The problem becomes even more complex when a single supplier is not able to provide entire ordered quantity, and allocation of order is needed among multiple suppliers.

6.1 Evaluation attributes

As alluded previously, we select and define several attributes based on which the alternative suppliers are evaluated from logistics 4.0 and resilience perspectives. Attributes are divided into two main groups: (1) quantitative and (2) qualitative as presented in Table 7. For attributes in the quantitative subset, large number of data is available in the form of continuous time series, and historically collected, which is characterized as non-time series data. These historically collected data is often stored graphically in logistics 4.0 environment due to the digitalization, cloud storage facilities and Internet of Things (IOT). Moreover, when visualized graphically, these data entail a great deal of actionable information that has been proven to be valuable while evaluating several sourcing options. As such, quantitative criteria are then sub-divided into two groups based on the type of data available as decision relevant information. We characterized that for inventory and delivery schedules, data are collected continuously and presented in time series as real-time visibility and end-to-end data sharing are considered as crucial aspects of logistics 4.0. On the other hand, data associated with supplier’s production capacity and cost are collected over the time and can be presented graphically. In case of other six attributes enlisted in Table 7, qualitative appraisal is given by the decision makers for each alternative supplier. All those attributes are so chosen that has been used to measure the resilience performance of the suppliers in the context of logistics 4.0.
| Attributes                  | Obj. | Description                                           |
|----------------------------|------|-------------------------------------------------------|
| Inventory level            | Max  | The quantity of inventory in stock and available for supply |
| Schedule of deliveries     | Min  | Time that supplier take to deliver the order to the company |
| Production capacity        | Max  | Quantity of the products that a supplier is capable to produce per day |
| Cost                       | Min  | Cost that is incurred by the company while purchasing the required quantity from a particular supplier. The cost here included per unit production and transportation cost |
| Digitalization             | Max  | Enabled by Web technologies, work flow tools, portals for customers, suppliers and employees, and information technology innovations targeted at supply chains and customer relationships (Rai, Patnayakuni, & Seth, 2006) |
| Traceability               | Max  | The ability to trace the origin of materials and parts, processing history and distribution or location of the product after delivery (Aung & Chang, 2014) |
| Supply chain density       | Min  | The quantity and geographical spacing of nodes within a supply chain |
| Supply chain complexity    | Max  | The number of nodes in a supply chain and the interconnections between those nodes |
| Re-engineering            | Max  | The corrective procedure for the incorporation of any engineering design change within the product |
| Supplier’s resource flexibility | Max  | The different logistics strategies which can be adopted either to release a product to a market or to procure a component from a supplier |

### 6.2 Results and sensitivity analysis

To test the practicability of our proposed model, we randomly generated a set of data in Appendix A. The numerical example includes five alternative suppliers that are evaluated with regards to four quantitative attributes and six qualitative attributes presented in Table 7. For each supplier, 500 records are collected as continuous time series in case of inventory level and delivery schedules (presented in Appendix A). In case of production capacity and cost, 300 records are used from historically collected data, which are presented in several pieces of graphs, making it easier to process this large quantity of data into actionable decision relevant information (presented in Appendix A). Data concerning each supplier against each qualitative criterion are collected from five decision makers who are assumed to have equal importance in decision making process.
The Closeness Coefficient ($CC$) and preferential ranking scores of the group of suppliers generated by the proposed model are presented in the Table 8 and Figure 12. As presented in Figure 12, supplier 1 has the highest $CC$ value, whereas lowest $CC$ value is observed for supplier 5. The highest $CC$ value indicates highest preferential ranking for that particular supplier, and corresponds to lowest number in the $R_i$. The lowest number in $R_i$ stands for highest preferred supplier.

| Supplier | $d^+$ | $d^-$ | $CC$ | $R_i$ |
|----------|-------|-------|------|------|
| $S_1$    | 1.24  | 1.09  | 0.467| 1    |
| $S_2$    | 1.32  | 1.08  | 0.450| 3    |
| $S_3$    | 1.31  | 1.06  | 0.448| 4    |
| $S_4$    | 1.31  | 1.08  | 0.451| 2    |
| $S_5$    | 1.43  | 0.90  | 0.388| 5    |

The detailed computation process is presented in Appendix B. Once the $CC$ values are obtained for each supplier, the MCGP is performed and solved with Lingo software. We assume that based on the previous experience, available resources and information, the decision makers has set different aspiration levels associated with different goals, which are presented below:

1) The total value created from procurement, defined as $T$ at least 200, and the more the better. It is signified as TVP constraint.
2) The total cost of procurement of is set in between $250000 and $280000, and the less the better. This correspond to budget constraint.
3) The lead time alternatively termed as delivery time is set in between 10 and 12 days, and the less the better. These parameters are used for delivery constraint.
4) Total procurement level should not be higher than 500, leads to order quantity constraint. With the abovementioned multiple goals the MCGP is formulated as follows:

\[
\text{Minimize } \sum_{i} (d_i^+ + d_i^-) + \sum_{j} (e_j^+ + e_j^-), \quad i = 1,2,3,4, j = 1,2,3
\]

Subject to:

0.467x_1 + 0.45x_2 + 0.448x_3 + 0.451x_4 + 0.388x_5 - d_1^+ + d_1^- \geq 200 \quad (1); TVP constraint

700x_1 + 1000x_2 + 600x_3 + 500x_4 + 650x_5 - d_2^+ + d_2^- = y_1 \quad (2); Budget constraint

\begin{align*}
y_1 - e_1^+ + e_1^- &= 250000 \quad (3); Budget aspiration level \\
250000 \leq y_1 \leq 280000 \quad (4); Budget aspiration level
\end{align*}

(11.01x_1 + 9x_2 + 14.03x_3 + 14.01x_4 + 14x_5)\sum_{1}^{n} x_n - d_3^+ + d_3^- = y_2 \quad (5); Delivery time constraint

\begin{align*}
y_2 - e_2^+ + e_2^- &= 10 \quad (6); Delivery time aspiration level \\
10 \leq y_2 \leq 12 \quad (7); Delivery time aspiration level
\end{align*}

\sum_{1}^{n} x_n - d_4^+ + d_4^- \leq 500 \quad (8); Order quantity constraint

x_n, d_i^+, d_i^-, e_j^+, e_j^- \geq 0 \quad (9)

After solving the formulated MCGP model, the results generated from Lingo are presented Table 9:

| Supplier | Allocated Order Quantity |
|----------|--------------------------|
| S_1      | 156                      |
| S_2      | 0                        |
| S_3      | 0                        |
| S_4      | 281                      |
| S_5      | 0                        |

Thus, in the final order allocation plan, the order quantity assigned to S_1 and S_4 are 156 and 281 respectively with the total order quantity of 437, while other suppliers are not assigned with any order quantity. Additionally, it is perhaps not surprising that based on the company’s available resources and information concerning the alternative suppliers, management may set different aspiration level for TVP goal ranging from most conservative to most optimistic estimation. Thus, the DSS system should be enable to propose alternative order allocation plan subject to the change of aspiration level associated with TVP goal. Therefore, we investigate several other instances by changing the aspiration level of TVP and assessed the effect of different TVP value on the order allocation plan as presented in Figure 13.
For a more conservative estimation of TVP value, the model assigns order to supplier 1 and supplier 2, with higher preference given to the first supplier. Even though, higher preference is given to supplier 1 over the range of TVP values within 170 to 190, quantity allocated to supplier 4 shows an increasing trend. Beyond that point, majority of the orders is allocated to supplier 4 with least preference given to supplier 1. After TVP value of 220, no order is allocated to supplier 1 anymore, while a stable order allocation plan is achieved by selecting supplier 4 and supplier 2 with highest priority given to supplier 4.

The preferential ranking score generated from F-MADM approach considers refined weights provided by the decision makers on attributes involved in alternative supplier selection process. This is essential as not all attributes are equally important in supplier evaluation scheme, and thus for making rational decisions, the differential weights are incorporated in our proposed F-MADM based DSS. However, often times cost factor associated with a procurement plan—and largely with a supplier, can turn out to be a vital attribute, requiring greater importance on cost over all other decision attributes. It is especially true for a logistics 4.0 company that mostly prefers efficiency from a supplier. On the contrary, prioritizing resilience performance of a supplier over cost may often be the dominating preference for type of logistics 4.0 company valuing greater ability against disruption, and thus enhancing visibility and responsiveness in satisfying customer needs even at the expense of greater cost. Reflecting on these two extremely opposite needs of the management, we investigate how to assist strategic decision makers in analyzing this trade-off while evaluating alternative suppliers for sourcing options. In what follows, we categorize the attributes mentioned in section 6.1 into two segments—considering cost alone as measure of efficiency while the rest of the attributes as-a-whole are considered as a holistic measure of resiliency for a supplier. We then perform TOPSIS separately on these two sets of attributes. Precisely saying, the $CC$ scores generated in the
context of resiliency will not include the suppliers’ information on cost attribute, which means in 5.11, \( j \neq C_4 \) \( \forall \) \( CC_{nP} \) and \( j = C_4 \) \( \forall \) \( CC_{nC} \); \( CC_{nP} \) and \( CC_{nC} \) refer to the \( CC \) associated with the resiliency and efficiency measure, respectively for \( n \)th supplier.

It is anticipated that supplier’s preferential ranking will change based on the differential importance on efficiency and resilience measures. To categorically distinguish this from the originally generated ranking score by F-MADM, we use Supplier’s Cost versus Resilience Index (SCRI) as a trade-off measure between resilience and efficiency, which is defined as follows:

\[
SCRI_n = \alpha CC_{nR} + (1 - \alpha) CC_{nC} \tag{6.1}
\]

Where \( SCRI_n \) is the index of \( n \)th supplier, and \( \alpha \) refers to the importance in the range of \([0, 1]\) given by the decision makers on resiliency performance. The lowest \( \alpha \) value is explained as decision maker’s lowest importance on resilience measure and vice-versa for cost (efficiency) measure. The corresponding \( CC \) values (also normalized) as measured by TOPSIS for cost attributes and resilience attributes are presented in Table 10 and Table 11:

**Table 10**

| Supplier | \( CC_{nP} \) | \( CC_{nC} \) | Normalized |
|----------|----------------|----------------|-------------|
| \( S_1 \) | 1.24            | 1.09            | 0.467       | 0.2119     |
| \( S_2 \) | 1.32            | 1.08            | 0.450       | 0.2043     |
| \( S_3 \) | 1.31            | 1.06            | 0.448       | 0.2031     |
| \( S_4 \) | 1.31            | 1.08            | 0.451       | 0.2048     |
| \( S_5 \) | 1.43            | 0.90            | 0.388       | 0.1758     |

**Table 11.**

| Supplier | \( CC_{nC} \) | Normalized |
|----------|----------------|-------------|
| \( S_1 \) | 0.45            | 0.21        |
| \( S_2 \) | 0.50            | 0.18        |
| \( S_3 \) | 0.48            | 0.19        |
| \( S_4 \) | 0.44            | 0.21        |
| \( S_5 \) | 0.45            | 0.21        |

Using normalized closeness coefficient and \( \alpha \) values, we then investigate the change of SCRI for different suppliers as presented in Figure 13. Supplier 4 has the highest SCRI value till \( \alpha = 0.5 \) beyond which supplier 1 starts dominating supplier 4 in the context of cost versus resilience trade-off. It points to the fact that when seeking resilience is less important compared to efficiency (signified by the lower \( \alpha \) values),
supplier 4 is highly preferred being the most efficient or cost effective supplier. The opposite is true for these two alternative suppliers for any values of \( \alpha \) beyond 0.5. Although supplier 5 has relatively higher SCRI value when higher importance is given on efficiency measure, its SCRI value decreases as higher importance is given on resilience measure. On the other hand, for supplier 2 and supplier 3, the SCRI values do increase with higher importance given on resilience measure. For several combination of resilience versus efficiency trade-off, the generated SCRI values are presented in the Table 12 in appendix B. Thus, our proposed DSS has demonstrated the managerial implication in terms of assisting the strategic decision makers to analyze the resiliency versus efficiency trade-off while evaluating and selecting alternative suppliers along with the corresponding order allocation plan.

![Analyzing cost (efficiency) versus resiliency trade-off](image)

Figure 13. Sensitivity analysis by assessing resiliency versus efficiency trade-off

7. Conclusion

Selection of resilient suppliers in the context of logistics 4.0 requires processing heterogeneous information originated from multiple qualitative and quantitative attributes that are conflicting in nature. Additionally, most of the qualitative attributes considered to measure the performance of resilient suppliers in logistics 4.0 are substantially different than those used in traditional supplier selection problem—a combined fact that limits the applicability of traditional Fuzzy-Based Supplier selection framework in the presence of heterogeneous DRI. This paper, to address this issue, presents a DSS that takes into account the inherent uncertainty of imprecise DRI to rank a set of alternative suppliers from resilient point of view. Particularly, we adapted and extended the TFN based TOPSIS to the framework of logistics 4.0 that can handle
qualitative information and also large number of quantitative information presented in the time series as well as graphical format. Using static and dynamic reliability index we modified the membership value to further take into account the uncertainty and impreciseness of triangular membership function. Because one supplier may sometimes fail to provide the entire ordered quantity, we develop a model leveraging MCGP to allocate order among alternative supplies. This model takes input from the supplier ranking score generated by proposed F-MADM approach. We also investigate the sensitivity of supplier’s resiliency versus efficiency measures with the change in importance of resiliency attributes (from resilience and logistic 4.0 perspective) and cost attribute. That way, we empower the decision makers to generate alternative index based on the differential importance on resiliency and cost attributes. We believe, the developed DSS will provide an effective and pragmatic approach to help stakeholders devise better sourcing decisions for logistic 4.0 industries. Future research can explore how to incorporate interdependencies among several attributes that often times possess hierarchically structured relationship to some extent. Further research can also be carried out to explore other techniques such as PROMETHEE along with other fuzzy sets such as Interval Valued Intuitionistic Fuzzy Sets (IVFS) to rank alternative suppliers supported by a mechanism for optimizing weights of the associated decision makers.

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Appendix A

Time-series Data

Figure 13. Time-series Data for Suppliers on Inventory ($C_1$)
Figure 14. Time-series Data for Suppliers on Delivery schedules ($C_2$)
Historically collected data presented in graphical format

Figure 15. Graphical Information for Suppliers on Non-time-series Criteria
**Linguistic Data:**

Table 13.
Linguistic Data (Performance Measurement and Criteria Weight)

| Supplier | $C_5$ (Digitalization) | $C_6$ (Traceability) |
|----------|-------------------------|----------------------|
| $S_1$    | DM1 VG DM2 VG DM3 VVG DM4 VG DM5 G | S1 VG VG VG VG VG VVG |
| $S_2$    | DM1 VG DM2 VVG DM3 EG DM4 VG DM5 G | S2 VG VG G MG MG |
| $S_3$    | DM1 EG DM2 VG DM3 VVG DM4 VG DM5 EG | S3 EG VVG VVG EG VG |
| $S_4$    | DM1 VG DM2 G DM3 MG DM4 VVG | S4 MG M M MG G |
| $S_5$    | DM1 M DM2 MG DM3 MG DM4 MG DM5 MB | S5 M M MG MG M |

| Supplier | $C_7$ (Supply Chain Density) | $C_8$ (Supply Chain Complexity) |
|----------|-----------------------------|---------------------------------|
| $S_1$    | DM1 VG DM2 VG DM3 G DM4 MG DM5 VVG | S1 G G VG VG VG |
| $S_2$    | DM1 M DM2 MG DM3 MG DM4 MG | S2 VVG VG VG VG VG |
| $S_3$    | DM1 G DM2 VG DM3 VVG DM4 VG DM5 G | S3 M G MG MG G |
| $S_4$    | DM1 VG DM2 VVG DM3 VG DM4 EG DM5 EG | S4 VG VVG VVG VVG VVG |
| $S_5$    | DM1 VG DM2 VVG DM3 VG DM4 VG DM5 VVG | S5 M MG MG MG M |

| Supplier | $C_9$ (Re-engineering) | $C_{10}$ (Supplier’s Resource Flexibility) |
|----------|------------------------|-------------------------------------------|
| $S_1$    | DM1 M DM2 MG DM3 M DM4 M DM5 MG | S1 VG VVG VVG VG VG |
| $S_2$    | DM1 M DM2 MB DM3 MB DM4 B | S2 M MG G M MG |
| $S_3$    | DM1 G DM2 VG DM3 G DM4 G DM5 G | S3 VG VVG VVG VVG VG |
| $S_4$    | DM1 M DM2 MG DM3 M DM4 M | S4 VG VVG VVG VG EG |
| $S_5$    | DM1 M DM2 MG DM3 MG DM4 MB | S5 G G M MG G |

| Criteria | Weight of the attribute |
|----------|-------------------------|
| $C_1$    | I VI EI I VI |
| $C_2$    | M I VI I M |
| $C_3$    | M M I M I |
| $C_4$    | I I VI I I |
| $C_5$    | I I VI VI I |
| $C_6$    | EI I EI EI I |
| $C_7$    | M M I I M |
| $C_8$    | I VI I I VI |
| $C_9$    | M UI M M UI |
| $C_{10}$ | I VI VI VI I |
Appendix B

Attributes concerning time series data

Based on the approach described in Step 1 and the original time-series data in Figure 13 and Figure 14, the possibility distribution in the form of triangular fuzzy number are generated as follows:

Figure 16. Graphical Triangular Fuzzy Number for Suppliers on $C_1$
Figure 17. Graphical Triangular Fuzzy Number for Suppliers on $C_2$

With the obtained graphical TFN, the numerical TFN could be constructed from Figure 16 and Figure 17 as:

Table 14. Numerical Triangular Fuzzy Number for suppliers on $C_1$ and $C_2$

| Supplier | C1 (Inventory) | C2 (Schedule of Deliveries) |
|----------|---------------|-----------------------------|
|          | a    | b    | c    | a    | b    | c    |
| S1       | 423.98| 441.04| 454  | 7.98 | 11.01| 15   |
| S2       | 459.98| 469.54| 480  | 5.98 | 9    | 12   |
| S3       | 441.98| 455.01| 470  | 10.98| 14.03| 17   |
| S4       | 404.98| 425.51| 445  | 11.98| 14.01| 16   |
| S5       | 424.98| 446.05| 459  | 9.98 | 14   | 18   |
Non-time-series Criteria:

Based on the computation process summarized in Step 2 and non-time series data in Figure 15, the original data could be extracted in the form of range value as follows:

Table 15.
Extracted range values for suppliers on non-time-series attributes

| $S_i$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ |
|-------|-------|-------|-------|-------|-------|
| $C_1$ | $C_1$ | $C_2$ | $C_1$ | $C_2$ | $C_1$ | $C_2$ | $C_1$ | $C_2$ |
| $R_{min}$ | $R_{max}$ | $R_{min}$ | $R_{max}$ | $R_{min}$ | $R_{max}$ | $R_{min}$ | $R_{max}$ | $R_{min}$ | $R_{max}$ |
| $R_1$ | 103 | 134 | 337 | 472 | 60 | 88 | 405 | 554 | 76 | 103 | 371 | 529 | 131 | 147 | 272 | 467 | 115 | 143 | 348 | 463 |
| $R_2$ | 96 | 136 | 310 | 478 | 60 | 90 | 400 | 555 | 76 | 110 | 361 | 531 | 128 | 152 | 345 | 455 | 112 | 144 | 314 | 474 |
| $R_3$ | 96 | 134 | 296 | 483 | 58 | 90 | 394 | 556 | 78 | 113 | 355 | 528 | 125 | 157 | 394 | 446 | 112 | 145 | 294 | 483 |
| $R_4$ | 96 | 135 | 295 | 483 | 59 | 89 | 391 | 556 | 79 | 113 | 351 | 528 | 128 | 158 | 270 | 458 | 111 | 144 | 283 | 489 |
| $R_5$ | 98 | 136 | 297 | 481 | 59 | 91 | 391 | 554 | 78 | 115 | 351 | 524 | 129 | 156 | 273 | 450 | 112 | 145 | 279 | 484 |
| $R_6$ | 100 | 136 | 300 | 478 | 60 | 91 | 391 | 554 | 77 | 115 | 354 | 522 | 129 | 157 | 283 | 442 | 111 | 146 | 282 | 478 |
| $R_7$ | 101 | 135 | 385 | 459 | 58 | 89 | 408 | 551 | 75 | 115 | 354 | 518 | 130 | 158 | 317 | 436 | 111 | 147 | 306 | 465 |
| $R_8$ | 103 | 135 | 300 | 473 | 58 | 88 | 420 | 547 | 75 | 113 | 357 | 511 | 131 | 157 | 326 | 462 | 111 | 148 | 311 | 382 |
| $R_9$ | 105 | 135 | 325 | 475 | 58 | 88 | 426 | 544 | 75 | 114 | 367 | 505 | 131 | 158 | 270 | 463 | 113 | 148 | 301 | 480 |
| $R_{10}$ | 110 | 136 | 301 | 482 | 60 | 87 | 430 | 536 | 75 | 113 | 363 | 529 | 134 | 156 | 270 | 454 | 114 | 149 | 287 | 486 |

With the extracted range values and the fuzzified frame of discernment presented in Figure 9, the TFN decision matrix could be constructed as Table 16:

Table 16.
Integrated Triangular Fuzzy Number for suppliers on non-time-series attributes

| Supplier | $C_3$ | $C_4$ |
|----------|-------|-------|
| $S_1$    | 102.98 | 117.23 |
| $S_2$    | 66.14  | 75.55  |
| $S_3$    | 81.25  | 95.04  |
| $S_4$    | 124.33 | 141.10 |
| $S_5$    | 113.44 | 128.67 |

According to Step 4 and Table 13, the Criteria Weight decision matrix could be constructed as:

Table 17.
Attribute weight decision matrix

| Criteria | Weight |
|----------|--------|
| $C_1$    | 0.50   |
| $C_2$    | 0.30   |
| $C_3$    | 0.30   |
| $C_4$    | 0.50   |
| $C_5$    | 0.50   |
The PIS and NIS matrix are generated based on function (5.6) and (5.7) in Step 5:

Table 18.
PIS and NIS for attributes

| Criteria | PIS |   |
|----------|----|---|
|          |    |   |
| $C_6$    | 0.50 | 0.78 | 1.00 |
| $C_7$    | 0.30 | 0.48 | 0.70 |
| $C_8$    | 0.50 | 0.64 | 0.80 |
| $C_9$    | 0.10 | 0.32 | 0.50 |
| $C_{10}$ | 0.50 | 0.66 | 0.80 |

SRCI values created for different $\alpha$ values and normalized $CC$ according to equation 6.1

Table 12
SSI based on $\alpha$

| Supplier/\alpha | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| $S_1$          | 0.208 | 0.208 | 0.209 | 0.209 | 0.210 | 0.210 | 0.210 | 0.211 | 0.211 |
| $S_2$          | 0.179 | 0.182 | 0.185 | 0.187 | 0.190 | 0.193 | 0.196 | 0.199 | 0.202 |
| $S_3$          | 0.192 | 0.194 | 0.195 | 0.196 | 0.197 | 0.198 | 0.200 | 0.201 | 0.202 |
| $S_4$          | 0.213 | 0.212 | 0.211 | 0.210 | 0.210 | 0.209 | 0.208 | 0.207 | 0.206 |
| $S_5$          | 0.208 | 0.204 | 0.200 | 0.197 | 0.193 | 0.190 | 0.186 | 0.183 | 0.179 |