Soft Computing (2025) 29:2845–2866
https://doi.org/10.1007/s00500-025-10578-z

SOFT COMPUTING IN DECISION MAKING AND IN MODELING IN ECONOMICS

A novel stochastic machine learning approach for resilient-leagile supplier selection: a circular supply chain in the era of industry 4.0

Bahar Javan Molaei[1] · Mohssen Ghanavati-Nejad[1] · Amirreza Tajally[1] · Mohammad Sheikhalishahi[1]

Accepted: 6 February 2025 / Published online: 28 April 2025

Abstract
Due to significant changes in supply chain environments and the importance of environmental and economic issues, various supply chain paradigms have been developed to address different challenges. As supplier evaluation and selection is one of the critical issues in supply chain management, in this paper a data-driven model is developed for this purpose. Considering the significance of different components in the case study of the home appliance industry, the leagile, resilience, circular economy, and Industry 4.0 paradigms are simultaneously considered for the first time in supplier evaluation. The key evaluation indicators in this study are recycled product, financial ability, waste management and delivery speed. The methodology used in this paper involves the use of data-driven stochastic model. In this regard, a stochastic VIKOR method has been developed based on scenarios, which improves evaluation effectiveness by considering different scenarios. Additionally, a neural network algorithm with a learning rate optimized using a genetic algorithm has been used to evaluate supplier performance. The findings demonstrate that the developed algorithm surpasses other algorithms, achieving an accuracy rate of 98 percent, and is effective for predicting supplier performance.

Keywords Supplier selection problem · Resilient supplier selection · Leagile supplier selection · Machine learning · Decision-making

1 Introduction

In the contemporary industrial landscape, characterized by intense competition, the importance of supply chain management has escalated, drawing unprecedented focus from both practitioners and academicians. The consensus among managers underscores the imperative of strategic planning within supply chains as a means to augment productivity, expand market presence, and secure a competitive edge (Rad et al. 2022). Within the broad spectrum of supply chain management disciplines, the process of supplier selection emerges as a pivotal element (Ivanov et al. 2022). The act of choosing among a vast array of suppliers is critical for effective supply chain management, influencing decisions related to product sales and market positioning. For larger enterprises, in particular, the strategy of supplier selection is instrumental in acquiring raw materials and products that meet the highest standards of quality and value (Fallahpour et al. 2021).

In recent years, with the development of digital technologies and the emergence of the Fourth Industrial Revolution, all businesses and supply chain structures have undergone changes, leading to the formation of Supply Chain 4.0 (Rostami et al. 2023; Sazvar et al. 2022). Supply Chain 4.0 has replaced the flow of products with digital information flow, altering the previous approach to evaluating supply chain efficiency and necessitating considering different components of the supply chain separately in modern businesses (Ivanov et al. 2022). According to reports published in the Statista database, the usage of Industry 4.0 technologies will more than double by 2030

✉ Mohammad Sheikhalishahi
m.alishahi@ut.ac.ir

Bahar Javan Molaei
bahar.javanmolaei@ut.ac.ir

Mohssen Ghanavati-Nejad
mohssen.ghanavati@ut.ac.ir

Amirreza Tajally
amirreza.Tajally@ut.ac.ir

[1] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

compared to 2023 (Lefranc 2023). Hence, in the assessment of various supply chain components, consideration of Fourth Industrial Revolution elements has become indispensable (Rostami et al. 2023).

In today's context, the concept of sustainable development in supply chains through circular economy has gained significant importance. Circular economy in supply chain management plays a crucial role in reducing resource waste (Yildizbasi and Arioz 2022). This economic approach focuses on the design and production of recyclable and renewable products, contributing to lower consumption of natural resources and less waste production, which enhances environmental sustainability in the supply chain (Wu et al 2023; Zarandi et al 2024). Furthermore, circular economy allows companies to shift away from resource-inefficient business models that lead to resource waste and move towards more sustainable and recyclable business models (Bai et al. 2022; ForouzeshNejad 2023). According to statistics, it is observed that the market for the circular economy worldwide will follow a completely upward trend in the coming years, highlighting the significance and attention to this component for supply chains (Topliceanu et al 2022).

Furthermore, in light of recent developments, the concept of supply chain resilience has gained renewed attention amid the challenges posed by the COVID-19 pandemic. The resilience of suppliers is of paramount importance as they have a direct influence on the business's performance and stability (Javan-Molaei et al 2024). Assessing the resilience of suppliers enables organizations to maintain their operations and satisfy customer demands under adverse conditions, including production interruptions, natural calamities, or market volatility (Rostami et al. 2023). Taking into consideration all mentioned elements, the appraisal of supply chain performance focuses on quality, speed, agility, and adaptability of the supply chain. In the realm of the home appliances industry, the adoption of circular economy principles and Industry 4.0 technologies plays a crucial role. Moreover, the principles of resilience and leagility are deemed essential in this sector due to the imperative for swift operational processes (ForouzeshNejad 2023).

Most supplier evaluation studies have been conducted based on expert-based approaches and questionnaire data (Chai et al. 2013; Govindan et al. 2015). However, with the development of data infrastructure in businesses, data-driven algorithms enhance decision-making accuracy in evaluations and performance forecasting of suppliers. Furthermore, considering uncertainty in supplier evaluation is imperative, given the highly complex business conditions in today's world.

Based on the explanations and motivations presented, this article proposes a data-driven random approach to address uncertainty, enabling a proactive evaluation of suppliers based on various indicators. The main research questions addressed in this study include:

- What are the evaluation indicators for home appliances industry suppliers based on resilience, leagile, Fourth Industrial Revolution, and circular economy?
- How are the weights and importance of each indicator determined?
- How are suppliers labeled in uncertain conditions and various scenarios?
- What is the data-driven random model for evaluating and predicting supplier performance?

The structure of the article is as follows; Sect. 2 provides a literature review. Section 3 presents the proposed solution method; Sect. 4 delves into the case study and outlines the metrics used for supplier evaluation. Section 5 presents the findings, and Sect. 6 concludes with managerial insights.

2 Literature review

2.1 Related works

In this section, articles related to supplier evaluation are examined. For example, Alavi et al. (2021) introduced a flexible decision support system designed to assist in choosing sustainable suppliers within a circular economy framework. This system lets users personalize and prioritize various factors such as economic, social, and cyclical aspects through the fuzzy best–worst method (BWM). The optimal supplier is then determined using a fuzzy inference system (FIS). The approach employs machine learning to continuously update and aggregate the criteria scores for suppliers after each selection round. Their methodology was demonstrated in a case study involving a company specializing in petrochemical materials. Tavana et al. (2021) evaluated suppliers based on a set of 12 digital-focused criteria. They employed the fuzzy best–worst method (FBWM) to assign weights to these factors. Subsequently, they utilized a comprehensive fuzzy optimization strategy, which amalgamated modified MULTIMOORA, COPRAS, and the fuzzy version of the Technique for order preference by similarity to ideal solution (TOPSIS), to rank the potential suppliers. Stojanović et al. (2022) determined key supplier selection criteria in an executable supplier framework. Supplier criteria were collected based on a questionnaire and input from various supplier companies, and the improved multi-objective fuzzy SWARA (IMF SWARA) approach was used for ranking key criteria in supplier selection. Hosseini et al. (2022) addressed the evaluation and selection of sustainable suppliers under demand uncertainty. They employed the combined BWM-Evidential Reasoning (ER) method for evaluation and ranking of suppliers in uncertain conditions. Furthermore, they proposed a bi-objective mathematical model to balance sustainability and economic cost under uncertainty using a novel integrated approach based on stochastic and dynamic programming.

Afrasiabi et al. (2022) introduced a comprehensive multi-criteria decision-making framework aimed at addressing the issue of selecting suppliers who are both sustainable and resilient. They examined 16 criteria across three dimensions of sustainability, with particular attention to factors related to resilience, including impacts from the COVID-19 pandemic. The weighting of these criteria was conducted through FBWM, and the ranking of suppliers was carried out using a combined GRA-TOPSIS approach. Sazvar et al. (2022) proposed a data-driven model for evaluating and selecting suppliers aligned with sustainability and resilience paradigms. They identified 22 criteria and used FBWM for their evaluation and weighting, along with FIS for determining the suppliers' performance rules. Machine learning algorithms were also utilized for constructing the supplier evaluation model.

Rostami et al. (2023) assessed suppliers of medical equipment by employing sustainable supply chain models. They introduced a novel methodology that blends multi-criteria decision-making techniques with ideal programming. Criteria such as production planning, agility, sustainability, and flexibility were highlighted as paramount, whereas factors related to digitalization were deemed less critical in this particular industry. The evaluation and comparison of supplier weightings were executed through the use of TOPSIS and VIKOR methods. Chai et al. (2023) utilized a fuzzy multi-criteria decision-making (MCDM) strategy that incorporates both time-based and geographical interval sets for assessing and choosing sustainable suppliers. To improve the precision of expert opinions, they implemented innovative fuzzy techniques. The methodology they introduced was specifically used to assess suppliers in the electric bicycle industry. Among the criteria deemed most significant in their research were economic strength, risk management capabilities, potential for job creation, and effectiveness in waste management.

Zhao et al. (2023) proposed an integrated approach based on the multi-criteria decision making (MCDM) theory set for selecting sustainable and resilient suppliers and allocating orders for distribution. In their two-level research, suppliers are first evaluated and selected, and then orders are allocated to them. Supplier evaluation in their study was performed using a developed VIKOR approach, and order allocation was solved using an ideal programming model. The most important evaluation criteria for suppliers are on-time delivery of products and crisis management. Muneeb et al. (2023) presented a model for selecting supplier-manufacturer and distributor for remanufactured products in the circular economy context. Since distributors play a role as suppliers of raw materials through reverse products in the circular economy, this model provides a comprehensive evaluation for them. The key criteria in the evaluation process of the proposed model include cost reduction, environmental impact reduction, and income maximization.

ForouzeshNejad (2023) focused on evaluating agile and sustainable suppliers in the era of the fourth industrial revolution. The author weighted the criteria using the rough best–worst method (RBWM) and then evaluated the suppliers using the multi-attributive border approximation area comparison (IR-MABAC) method. The most important criteria in the evaluations conducted in the study are production flexibility, cost, reliability, smart factory, and quality. Nayeri et al. (2023a, b) presented a data-driven model for evaluating suppliers in the supply chain and allocating orders for distribution to them. The proposed method for supplier evaluation is SBWM, and then, using data-driven algorithms, supply chain network parameters were estimated considering uncertainty, and order allocation to suppliers was carried out. The key identified indicators in their study include cost, agility, and pollution production. Hajiaghaei-Keshteli et al 2023 developed a new method for selecting green suppliers in the food industry based on TOPSIS. They have stated that the use of green supply chain criteria in supplier evaluation is of high importance and significantly aids in reducing waste and optimizing energy consumption and costs. Their developed solution method (PF-TOPSIS) performs better than the classic TOPSIS method. Tavakoli et al. (2023) have presented a fuzzy decision-making approach based on Markov for evaluating and selecting resilient and sustainable suppliers based on customer service criteria. Using a hybrid method of fuzzy best–worst and Markov, they calculated the weights of the indices and then evaluated the suppliers using the QFD method. The most important supplier evaluation criteria in their study include cost, quality, timely delivery, responsiveness, and service level.

Sheykhzadeh et al. (2024) tackled the supplier evaluation in the pharmaceutical sector through the lens of green, resilient, and agile attributes. To achieve this, the team first identified key indicators and alternatives. They then crafted a hybrid fuzzy methodology that integrates the fuzzy best–worst method (BWM) with the additive ratio assessment technique, allowing for the calculation of indicator weights and the evaluation of suppliers. Liang et al. (2024) concentrated on assessing raw material providers by employing resiliency and digitalization metrics through a model based on machine learning. With an emphasis on the significance of blockchain technology, they formulated a two-stage approach for the evaluation of suppliers, aimed at bolstering supply chain resilience.

In addition to studies in the field of supplier evaluation, several studies in the area of multi-criteria decision-making methods are reviewed. For instance, Dammak et al. (2015) explored and compared multi-criteria decision-making methods such as TOPSIS, AHP, VIKOR, and their integration with fuzzy structures. Their findings indicate that fuzzy structures can aid MCDM methods in improving accuracy and performance. Uluçay et al. (2018) developed a trapezoidal fuzzy approach and its application in multi-criteria decision-making problems. Their findings also demonstrate that trapezoidal fuzzy approaches, when combined with MCDM methods, can enhance the efficiency of the model. Ulucay (2020) a new method based on multi-criteria decision-making has been proposed for trapezoidal fuzzy numbers. They introduced a new weighted similarity function for trapezoidal fuzzy numbers, which examines the similarity between options. Their method was implemented on a numerical example, and its accuracy was demonstrated. Ejegwa and Zuakwagh (2022) examined modified fuzzy hybrid methods in various approaches. Their comparisons show that the use of fuzzy approaches in addressing uncertainties can be beneficial and increase evaluation accuracy. Voskoglou and Broumi (2022) developed a hybrid method for assessing inductive reasoning skills. Their investigations and the developed method show that use in fuzzy or grey approaches can help increase model accuracy in uncertain conditions. Table 1 provides a summary of the literature review.

2.2 Research gaps

Based on the reviews conducted in the literature, it can be observed that there is no study that simultaneously addresses the evaluation of suppliers based on the criteria of Leagile, Resilience, Industry 4.0, and Circular Economy. In general, the concepts of Industry 4.0 and Circular Economy are relatively new topics in the supply chain context, and they have recently gained attention from researchers in the supply chain field. On the other hand, in studies related to supplier evaluation, less attention has been paid to uncertainty in the assessments. In this study, a novel scenario-based and stochastic approach for supplier evaluation is developed, and ultimately, a predictive model for supplier performance is presented using the developed neural network algorithm. Based on the stated explanations, the main innovations of this study are as follows:

- The simultaneous integration of Leagile, Resilience, Industry 4.0, and Circular Economy criteria in supplier evaluation;
- Supplier evaluation in the home appliance industry based on combined criteria;
- Development of the Stochastic VIKOR method with scenario-based analysis, designed by considering various scenarios for supplier evaluation, which increases the accuracy of assessment and prioritization;
- Development of the ANNG hybrid method, a neural network based on a genetic algorithm with an optimized learning rate, used in supplier evaluation.

3 Methodology

3.1 Stochastic FBWM

As aforementioned, in this study, the SFBWM has been employed to calculate the weight of indicators. In this section, we have briefly defined this approach. The SFBWM is the extended form of the traditional BWM to deal with uncertain environment. Indeed, this efficient approach has been developed to tackle both event-based and epistemic uncertainties (Nayeri et al. 2023a, b). The main advantages of this method are as follows (Nayeri et al. 2023a, b): (i) this approach enhances the reliability of the outputs, (ii) this method deals with different types of uncertainties, (iii) this method easily can combine with different methods. In the following, we have described the steps of the SFBWM. Suppose that there are S scenarios indexed by s and N criteria indexed by n. The probability of each scenario is denoted by PS_s such that $\sum_s PS_s = 1$. Moreover, let B and W respectively represent the Best and the Worst indicators determined by decision-makers. By considering $\widetilde{a}_{Bjs} = \left(l_{Bjs}, m_{Bjs}, u_{Bjs}\right)$ as the fuzzy comparison vector between the best indicator and the others, $\widetilde{a}_{jWs} = \left(l_{jWs}, m_{jWs}, u_{jWs}\right)$ as the fuzzy comparison vector between the worst indicator and the others, and $\widetilde{ws}_j = (l^w_{js}, m^w_{js}, u^w_{js})$ as the fuzzy weights of the indicators, the mathematical formulation of the SFBWM can be written as Model (1) (Nayeri et al. 2023a, b) where w_j is weight of j th criterion and $\widetilde{\xi}_s^{\,*} = (k_s^*, k_s^*, k_s^*)$.

Table 1 Literature review summary

Study	Aspect				Uncertainty	Methodology	Case study
	Leagile	Resiliency	Industry 4.0	Circular economy			
(Alavi et al 2021)				*		FBWM—FIS	Petrochemical
(Tavana et al 2021)			*			FBWM—MULTIMOORA—TOPSIS	–
(Afrasiabi et al 2022)		*		*		FBWM—GRA-TOPSIS	Medical Equipment
(Tushar et al 2022)				*		FAHP-PROMETHEE II	Construction
(Hosseini et al 2022)				*	*	BWM-ER	–
(Stojanović et al. 2022)						IMF SWARA	O&G industry
(Sazvar et al 2022)		*		*		FBWM-FIS-ML	Medicine
(Chai et al 2023)				*		Fuzzy MCDM	Electric bicycles
(Rostami et al 2023)	*	*	*			GP-BWM	Medical Equipment
(Zhao et al 2023)		*				MCDM—Goal Programming	–
(Muneeb et al 2023)				*		MODM	Refrigerator production
(ForouzeshNejad 2023)	*		*	*		RBWM/IR-MABAC	Medical Equipment
(Nayeri et al 2023a, b)	*	*			*	FSBWM—DDFRS	Medical Equipment
Hajiaghaei-Keshteli et al 2023				*		PF-TOPSIS	Food industry
(Tavakoli et al 2023)		*		*		FBWM-Markov-QFD	Online marketplace
Sheykhzadeh et al. (2024)	*	*				BWM—ARAS	Pharmaceutical supply chain
Liang et al. (2024)		*	*			Robustness PROMETHEE	–
This study	*	*	*	*	*	Stochastic BWM—Stochastic VIKOR—ANN-Genetic (ANNG)	Home Appliances

$$
\begin{aligned}
&\text{Minimize } \sum_s PS_s \tilde{\xi}_s^* \\
&\text{subject to} \\
&\left| \frac{\left(l_{Bs}^w, m_B^w, u_{Bs}^w\right)}{\left(l_{js}^w, m_{js}^w, u_{js}^w\right)} - \left(l_{Bjs}, m_{Bjs}, u_{Bjs}\right) \right| \leq \left(k_s^*, {}^*, k_s^*\right) && \forall j, s, \\
&\left| \frac{\left(l_{js}^w, m_{js}^w, u_{js}^w\right)}{\left(l_{Ws}^w, m_{Ws}^w, u_{Ws}^w\right)} - \left(l_{jWs}, m_{jWs}, u_{jWs}\right) \right| \leq \left(k_s^*, k_s^*, k_s^*\right) && \forall j, s, \\
&\sum_{j=1}^{n} R\left(\widetilde{ws}_{js}\right) = 1 && \forall s, \\
&l_{js}^w \leq m_{js}^w \leq u_{js}^w && \forall j, s, \\
&w_j = \sum_s P_s R\left(\widetilde{ws}_{js}\right) && \forall j, \\
&l_{js}^w \geq 0 && \forall j, s,
\end{aligned}
\tag{1}
$$

It should be noted that in each scenario, the comparison vectors can be formed based on Table 2.

Finally, the consistency ration (CR) can be calculated according to Table 3 and Relation (2).

Table 2 Linguistic Variables in the SFBWM (Guo & Zhao 2017)

Language terminology	Membership function
Fundamental significance (FS)	(3.5, 4, 4.5)
Extremely significant (ES)	(2.5, 3, 3.5)
Moderately significant (MS)	(1.5, 2, 2.5)
Somewhat significant (SS)	(0.6667, 1, 1.5)
Equally significant (ES)	(1, 1, 1)

Table 3 Values defined for the CI (Guo & Zhao 2017)

	(ES)	(SS)	(MS)	(ES)	(FS)
$\widetilde{a}_{BW}$	(1, 1, 1)	(0.667, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)
CI	3.00	3.80	5.29	6.69	8.04

$$CR = \frac{\xi^*}{CI} \tag{2}$$

3.2 Stochastic scenario-based VIKOR (SVIKOR)

The VIKOR method represents an advanced approach for optimizing multiple attributes and facilitating consensus in decision-making processes. Introduced by Aprikovich in 1998, its primary aim is to identify the best possible outcomes for decisions involving multiple criteria. VIKOR is used to assess and prioritize alternatives by evaluating them against a range of performance metrics, striving to bring each option as close as possible to an ideal solution for every criterion. The ranking of alternatives is then based on how closely they match this ideal standard (Abdel-Baset et al. 2019).

There are several variations of the VIKOR method, including the application of fuzzy logic. In our study, we introduce the Stochastic VIKOR method for the first time, broadening the methodology's utility to include situations marked by uncertainty and variability. This novel approach constructs various scenarios, each with its specific weighting, influencing the overall ranking of alternatives. The decision-making process thus incorporates multiple potential conditions and scenarios, making the selection of the best alternative more reflective of complex real-world decision scenarios. Generally, the structure of the Stochastic VIKOR method is such that a number of n scenarios are selected according to different conditions for evaluating options, and then the weights of the evaluation indicators are chosen differently for each scenario. Based on the weights of the indicators in each scenario, different values are determined for each option for each indicator, based on which the evaluation of options is carried out in the target scenario. Subsequently, the final ranking of the options is determined from among the evaluations of all scenarios, in accordance with the weight and significance of the occurrence of each scenario.

The procedural steps for implementing the SVIKOR method are delineated as detailed below:

1. Constructing the matrix of decision:

At this point, we construct the decision matrix for the SVIKOR method, focusing on its unique attribute of evaluating alternatives through varied scenarios, making the decision-making inherently scenario-dependent. Imagine $Sr = \{sr_1, sr_2, \ldots, sr_s\}$ as the set of scenarios relevant to our problem, where each scenario Sr_s is associated with a probability Ps_s of occurring. Moreover, consider $C = \{c_1, c_2, \ldots, c_i\}$ as the criteria set relevant to the decision-making process and $A = \{a_1, a_2, \ldots, a_j\}$ as the alternatives being evaluated. The performance of alternative *'j'* under criterion *'i'* in scenario *'s'* is represented by the score x_{jis}, laying the foundation for the SVIKOR decision matrix. When decisions involve multiple stakeholders, their individual decision matrices can be consolidated, as demonstrated, for instance, in Table 4.

2. Standardize the matrix of decision.

In the next step, the compiled decision matrix is subjected to a process of normalization or rescaling. There are multiple methods available for carrying out this normalization, and for our study, we selected a particular technique to apply.

$$n_{jis} = \frac{x_{jis}}{\sqrt{x_{jis}^2}} \tag{3}$$

3. Construct the weighted normalized matrix of decision:

During this stage, the goal is to create a scaled and weighted evaluation matrix. This process entails multiplying each column, representing a specific scenario, by the probability of the scenario's occurrence (Ps_s) and the weight attributed to the related criterion. Assume $W = \{w_1, w_2, \ldots, w_i\}$ as the weights designated for each criterion.

$$f_{jis} = Ps_s.n_{jis}.w_i \tag{4}$$

Table 4 VIKOR decision matrix

	c_1			c_2			$\ldots$	c_i		
	sr_1	$\ldots$	sr_s	sr_1	$\ldots$	sr_s		sr_1	$\ldots$	sr_s
a_1	x_{111}	$\ldots$	x_{11s}	x_{121}	$\ldots$	x_{12s}	$\ldots$	x_{1i1}	$\ldots$	x_{1is}
a_2	x_{211}	$\ldots$	x_{21s}	x_{221}	$\ldots$	x_{22s}	$\ldots$	x_{2i1}	$\ldots$	x_{2is}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
a_j	x_{j11}	$\ldots$	x_{j1s}	x_{j21}	$\ldots$	x_{j2s}	$\ldots$	x_{ji1}	$\ldots$	x_{jis}

4. Identify the negative and positive points:

In the fourth step, the identification of both positive and negative ideal points takes place. For a criterion where higher values are favored (positive criterion), the positive ideal point in a given scenario is identified by the highest value in that scenario's column. On the other hand, for a criterion considered negative (where lower values are better), the positive ideal point is the lowest value in the column of that scenario. The process is reversed for determining the negative ideal points. For example, in the case of a positive criterion, the method to calculate both positive and negative ideal points is as described.

$$f_s^+ = \max\{f_{ijs}\} \tag{5}$$

$$f_s^- = \min\{f_{ijs}\} \tag{6}$$

5. Compute the utility regret (R) and (SS) metrics for criterion:

During this phase, the metrics for utility and regret are derived based on specified formulas.

$$L_{js} = \sum_i \frac{f_s^+ - f_{ijs}}{f_s^+ - f_s^-} \tag{7}$$

$$SS_j = \sum_s Ps_s.L_{js} \tag{8}$$

$$T_{js} = \max_i \left\{ \frac{f_s^+ - f_{ijs}}{f_s^+ - f_s^-} \right\} \tag{9}$$

$$R_j = \sum_s Ps_s.T_{js} \tag{10}$$

6. Computing the values of the VIKOR index (Q):

At this point, the calculation of the Q index value is performed using a particular formula. It is important to highlight that in this context, v symbolizes the overall utility.

$$Q_j = v.\left[\frac{SS_j - SS^*}{SS^- - SS^*}\right] + (1-v).\left[\frac{R_j - R^*}{R^- - R^*}\right] \tag{11}$$

$$SS^- = \max\{SS_j\}, SS^* = \min\{SS_j\} \tag{12}$$

$$R^- = \max\{R_j\}, R^* = \min\{R_j\} \tag{13}$$

A key aspect involves aggregating the Q index across all scenarios. In this process, each individual Q value is expanded by the corresponding probability of the scenario's happening. The final Q value is then determined by summing up these weighted Q index values.

7. Rank alternatives based on Q, R, and S values:

In this step, the options and items are ranked in descending order based on their relevant S, R, and Q values. The alternative denoted as a' is suggested as the optimal compromise solution, ranking highest based on the minimum Q value and subject to two specific conditions. The first of these conditions pertains to an acceptable advantage, as defined by a particular formula.

$$Q(a'') - Q(a') \geq \frac{1}{i-1}, i : numberofalternatives \tag{14}$$

The alternative marked as a'' holds the secondary rank in the Q ranking list. The next condition stipulates an acceptable level of stability in the decision-making process. To meet this, the alternative a' should also occupy the top rank in either the S or R ranking lists, or ideally both. The stability of this ranking remains constant throughout the Decisional process.

If either of these conditions is not satisfied, a set of consensus-based solutions is recommended:

- Alternatives a' and a'' are proposed if only the second condition is not met.
- Alternatives $a', a'', a''', \ldots, a^m$ are proposed if the first condition is not met.

The maximum value for *'m'* in this context is defined using *a* specific equation.

$$Q(a^m) - Q(a')(\frac{1}{i-1}) \tag{15}$$

One should observe that the stochastic VIKOR approach had been previously introduced (Tavana et al 2018), but their model considered randomness by taking into account the probability for each value. However, in this study, the presented stochastic VIKOR approach is defined based on scenarios, allowing for the design of various scenarios without any limitation. As a result, it enables more detailed and extensive data-based evaluations.

3.3 Artificial neural network with genetic algorithm (ANNG)

After determining the supplier labels using the combined SBWM-SVIKOR approach, an artificial neural network (ANN) model is presented for the evaluation of suppliers. Artificial neural networks are a pattern of information processing that seeks to mimic the behavior of biological neural systems such as the human brain. An artificial neural network (ANN) is comprised of a multitude of interlinked computational units, often referred to as neurons. These units collaborate to tackle specialized tasks (Abiodun et al. 2019; Khameneh et al 2023).

Neural networks are structured with distinct components. Essentially, the neural network structure consists of several main layers, and each layer is comprised of a number of computational units or neurons. Neurons within the layers are interconnected, and they have their specific weights (Alizadeh et al. 2023; Ilbeigi et al. 2020). One of the very important parameters in neural network algorithms is the learning rate. The learning rate plays a crucial role in neural network algorithms and is considered one of the key parameters in the machine learning process. This rate determines how much the network's weights change at each step of training. In other words, the learning rate controls the update of weights in the neural network based on the training data and the calculated error. Optimizing the learning rate can help reduce training time and increase the efficiency of the network in achieving more accurate results. There are various manual methods for optimizing the learning rate in neural network algorithms, and the use of metaheuristic algorithms can enhance the accuracy of this optimization. For this reason, in this study, the optimization of the learning rate using the genetic algorithm has been employed. The primary components of a neural network include (Fan et al. 2021; Gowdhaman and Dhanapal 2022):

Layers: Neural networks typically consist of three main layers:

- Input layer: This layer is responsible for receiving input data. Each neuron in this layer is usually assigned to one of the input features.
- Hidden layer: The layers within the network analyze the data and uncover latent attributes. The quantity of hidden layers, as well as the count of neurons within each layer, can differ.
- Output layer: This layer generates the final output of the network. Each neuron in this layer typically provides the result of a specific class or output.

2. Weights: Each connection between two neurons has a weight associated with it, representing the influence or significance of one neuron on another. Throughout the training process, these weights are adjusted by the algorithm to help the network learn patterns and relationships within the data, enhancing its predictive accuracy.

3. Activation function: The activation function is applied to the output of neurons to transform the computed values into specific values. The activation function helps the network provide accurate responses and handle non-linear problems.

4. Loss function: The loss function is a measure that evaluates the difference between the network's output and the expected output (true labels). The goal of the network during the training process is to minimize the value of the loss function to achieve better results.

One of the important components in a neural network is the learning rate. In neural networks, the learning rate is a parameter related to the training process of the network and determines the amount of weight adjustments for each training iteration (Smith & Topin 2019; Chaturvedi et al 2023). The learning rate is directly applied to the network during the training process, and in each iteration of training, the weights are updated based on it. Notably, various approaches are available for optimizing this learning rate, and in this study, it is optimized using a genetic algorithm.

The process of optimizing the learning rate with genetics is as follows:

1. Definition of the objective function: The objective function serves as a metric to evaluate the quality of different learning rates during the optimization process. This objective function can be a measure such as accuracy or error, which needs to be minimized or maximized to find the optimal learning rate.
2. Representation of each learning rate as a gene: In this step, each learning rate is represented as a gene. These genes can be real numbers representing the range of allowable values for the learning rate.
3. Creating an initial population: Initially, a random population of genes is created. This population may include a large number of genes representing different values of the learning rate.
4. Evaluating the performance of the population: Each gene in the population is evaluated using the objective function, and its performance in the population is recorded.
5. Selection: Genes that exhibit superior performance, as determined by the objective function, are more likely to be chosen. The common method employed for this type of selection is often Tournament Selection.
6. Crossover: In this step, the selected genes are combined to produce the next generation. The crossover is performed using the Single-Point Crossover method.
7. Mutation: With a low probability, some genes may undergo changes. This mutation is usually introduced randomly and aims to maintain diversity in the population to avoid getting stuck in local minima.
8. Repeat steps 4–7: These steps are repeated until termination conditions, such as a specified number of iterations or achieving desirable results, are met.
9. Selecting the best gene: Ultimately, the optimal learning rate is selected based on the performance of the best gene (as the optimal outcome) and is used for training the network.

Overall, the structure of these steps is illustrated in Fig. 1.

It should be noted that numerous papers have focused on combining genetic algorithms and neural networks to optimize their parameters. In supplier evaluation studies, data-driven hybrid approaches have been less frequently

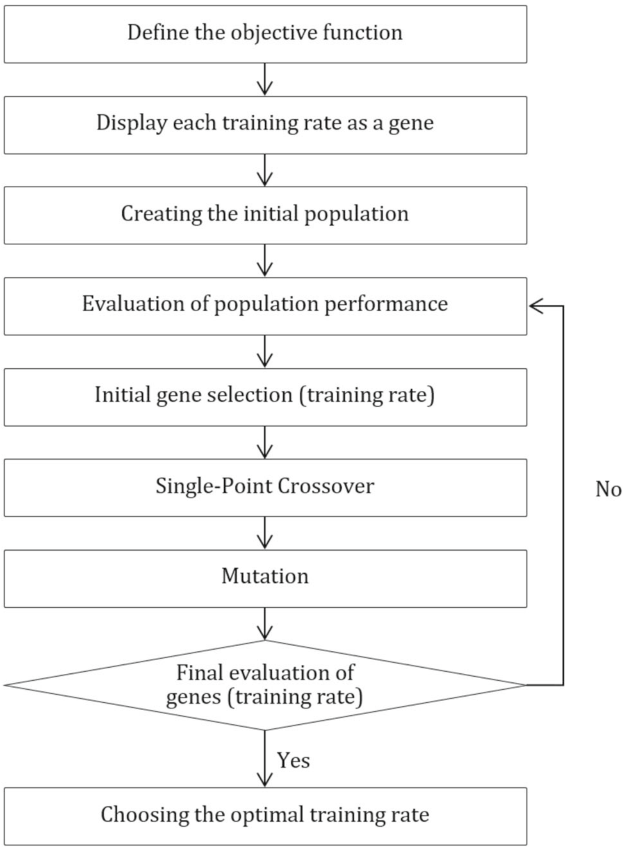


Fig. 1 Optimizing neural network training rate with genetics

explored. This study focuses on such an approach to provide a more accurate assessment of suppliers based on real data.

3.4 Hybrid method

In this paper, initially, the supplier evaluation indicators were weighted using the SFBWM method, and then suppliers were prioritized using the SVIKOR method. The aim of combining these two methods and developing the SVIKOR approach is to account for various scenarios in weighting indicators and evaluating suppliers, which, by considering different conditions, enhances the performance and accuracy of the evaluation. By integrating the SFBWM and SVIKOR methods, unlabeled data were labeled and used as the required dataset for building the ANNG model. The data-driven nature of the developed model stems from the use of documented supplier data in their evaluation and is based on machine learning algorithms (ANNG). The reason for its scenario-based approach and its ability to handle uncertainty is the definition of various scenarios in labeling the data and applying different conditions in the data labeling process. According to the explanations given, the combined method and steps used in this study are shown in Fig. 2.

4 Case study

The case study of this article pertains to a home appliance manufacturing factory that had production facilities in three regions: Tehran, Qom, and Isfahan. Various suppliers from different parts of Iran provide the required raw materials. Generally, for manufacturing plants located in three provinces, it is crucial that suppliers can deliver products and raw materials to the factory under different conditions, including crisis events such as COVID-19 and natural disasters like floods and earthquakes; hence, supplier resilience is of great importance. On the other hand, the quality and appropriate speed in delivering raw materials and required parts from suppliers are also highly important, with leagile criteria being considered for suppliers. One of the significant aspects that manufacturers pay attention to is the consideration of environmental components and macroeconomic factors, which is why supplier evaluation based on circular economy principles is also addressed. The topic of the circular economy in various dimensions of supply, production, and distribution chains has attracted the attention of many researchers and organizations in recent years. Additionally, due to changes in supply chain environments resulting from digital transformation and Industry 4.0, where the key components are data usage, artificial intelligence, and extensive information sharing, Industry 4.0 indicators are also crucial in analyzing and evaluating suppliers. The importance of each set of indicators varies under different conditions and scenarios, and for this reason, scenario-based structures are used in evaluating indicators to provide a more accurate assessment. The overall geographical structure of the case study is illustrated in Fig. 3.

In this regard, according to the structure of the case study and the desired paradigms in this article, the evaluation indicators are described in Tables 5, 6, 7, 8.

The dataset used in this study to develop the data-driven model consists of 720 records representing supplier behavior across different time periods. Each record reflects the evaluation of a supplier based on 17 diverse indicators. The structure of the dataset is such that each record corresponds to a specific time period for a supplier, with 17 features representing the evaluation indicators. These indicators include Quality (C01), Cost (C02), Delivery Speed (C03), Transportation (C04), Returned Products (C05), Robustness (C06), Cooperation (C07), Backup Supplier (C08), Supply Capacity (C09), Greenhouse Gas Emissions (C10), Financial Ability (C11), Waste Management (C12), Recycled Products (C13), Information

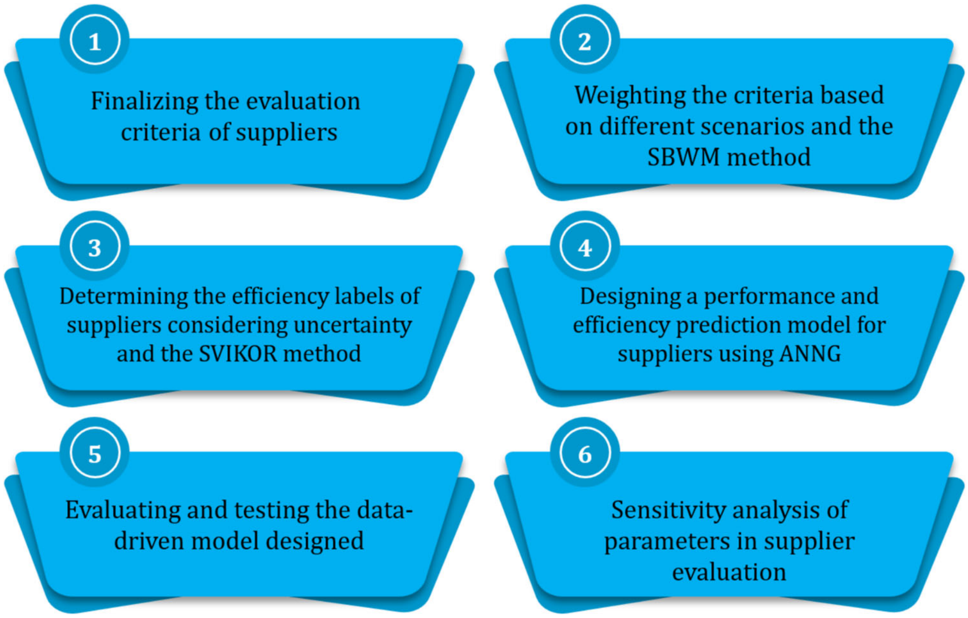


Fig. 2 The steps of the hybrid method

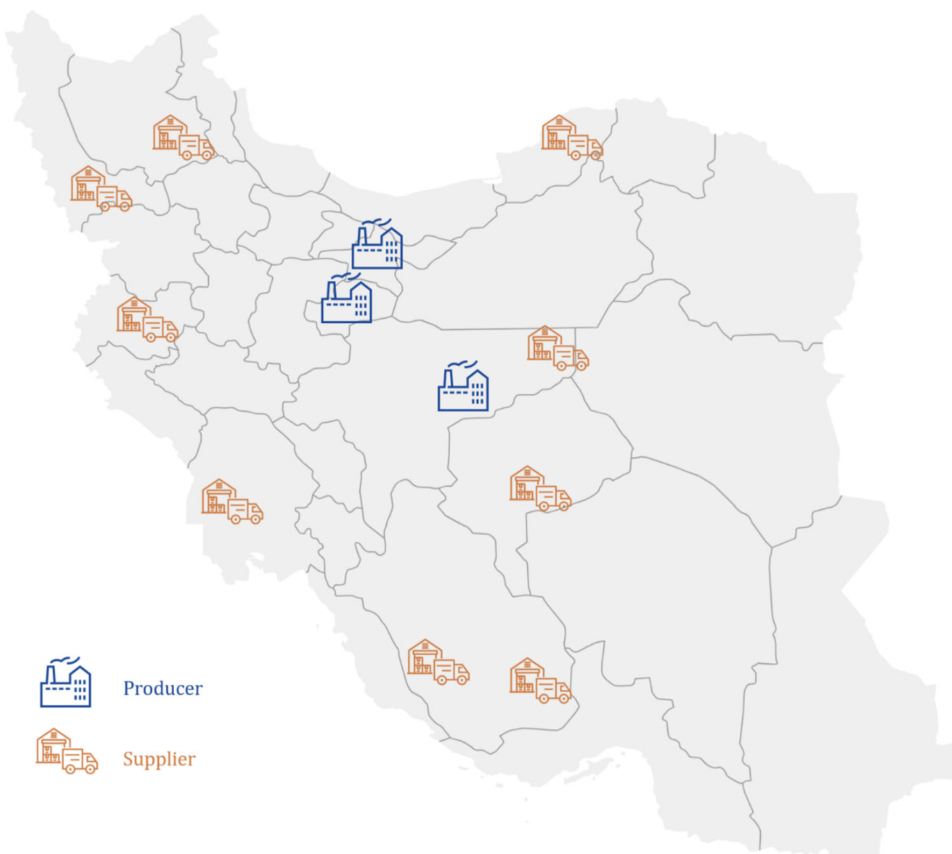


Fig. 3 Case study structure

Sharing (C14), Information Security (C15), Business Intelligence (C16), and Smart Production (C17). Each indicator provides unique insights into the performance and capabilities of the suppliers.

Statistical analysis of these indicators reveals that the Quality indicator (C01) has an average value of 6.64, with a minimum of 4.84 and a maximum of 10.16. The Cost indicator (C02) has an average value of 168,283.97, ranging from 23,655.68 to 683,628.88. Delivery Speed (C03)

Table 5 Leagile criteria

Criteria		Definition	References
C01	Quality	Supplier's ability to provide quality products	Rostami et al 2023
C02	Cost	The cost of the supplier's products	Rostami et al 2023
C03	Delivery speed	The supplier's delivery speed from the moment of ordering	ForouzeshNejad 2023
			Nayeri et al 2023a, b
C04	Transportation	The supplier's adaptability and dependability in the realm of transportation	Galankashi et al 2021
			ForouzeshNejad 2023
C05	Returned	Percentage of products returned	ForouzeshNejad 2023

Table 6 Resilience criteria

Criteria		Definition	References
C06	Robustness	Supplier's ability to manage risk and crisis	Rostami et al 2023
			ForouzeshNejad 2023
C07	Cooperation	The supplier's capacity for effective partnership collaboration	Nayeri et al 2023a, b
			Sazvar et al 2022
C08	Contingency Supplier	The supplier's proficiency in establishing agreements with backup vendors	Rostami et al 2023
			Nayeri et al 2023a, b
C09	Supply capacity	The supplier's ability to supply raw materials	ForouzeshNejad 2023

Table 7 Circular economy criteria

Criteria		Definition	References
C10	Greenhouse Gas Mitigation	The supplier's competence in monitoring and minimizing greenhouse gas emissions	Kusi-Sarpong et al 2021
C11	Financial ability	The amount of capital and financial base of the company	Dey et al 2022
			Sazvar et al 2022
C12	Waste Handling	The supplier's expertise in managing and diminishing waste production	Rostami et al 2023
C13	Recycled product	The percentage of the product that can be recycled	Kusi-Sarpong et al 2021

Table 8 Industry 4.0 criteria

Criteria		Definition	References
C14	Information sharing	The supplier's skill in disseminating information effectively with collaborators	Rostami et al 2023
C15	Information security	The level of information and data security in the organization	Rostami et al 2023
			Çalık, 2021
C16	Business intelligence	The percentage of order registration processes that are done intelligently	ForouzeshNejad 2023
C17	Smart production	The Percentage of production processes that are done intelligently	Çalık, 2021

has an average of 7.97, with a minimum of 5.81 and a maximum of 12.19. The Transportation indicator (C04) has an average of 17.01, with values ranging from 12.41 to 26.03. The Returned Products indicator (C05) has an average value of 0.85, with a minimum of 0.77 and a maximum of 0.99. Robustness (C06) has an average of

Table 9 Criterion weightings

Aspect	Aspect's weight	Criteria	Criteria's initial weight	Criteria's final weight ($Aspect's\,weight\times Criteria's\,initial\,weight$)
Leagile	0.285714	Quality	0.224615	0.064176
		Cost	0.193846	0.055385
		Delivery speed	0.233846	0.066813
		Transportation	0.166154	0.047473
		Returned	0.181538	0.051868
Resiliency	0.232653	Robustness	0.224138	0.052146
		Cooperation	0.228448	0.053149
		Backup supplier	0.284483	0.066186
		Supply capacity	0.262931	0.061172
Circular economy	0.273469	Greenhouse gas emission	0.224335	0.061349
		Financial ability	0.254753	0.069667
		Waste management	0.250951	0.068627
		Recycled product	0.269962	0.073826
Industry 4.0	0.208163	Information sharing	0.242266	0.050431
		Information security	0.253448	0.052758
		Business intelligence	0.259038	0.053922
		Smart production	0.245248	0.051052

Table 10 The values of CRs

Step	CR
Aspects	0.05651
Leagile criteria	0.06325
Resiliency criteria	0.05954
Circular economy criteria	0.06132
Industry 4.0 criteria	0.04324

Table 11 The outputs of the SVIKOR method and labeling

	Qj	*Label*
S1	0.6403492	Efficient
S2	0.8187356	Inefficient
S3	0.5999819	Efficient
S4	0.2679577	Highly efficient
S5	0.6932657	Efficient
S6	0.2298167	Highly efficient
S7	0.8908996	Inefficient
S8	0.1616147	Highly efficient
S9	1.000000	Inefficient
S10	0.4944887	Efficient

3,000.30, with values ranging from 431.04 to 12,132.88. The Cooperation indicator (C07) has an average of 2,507.50, with a minimum of 216.76 and a maximum of 11,084.24. The Backup Supplier indicator (C08) has an average value of 5.45, ranging from 0.73 to 10.27. Supply Capacity (C09) has an average of 490.96, with values ranging from 169.77 to 1,105.38. Greenhouse Gas Emissions (C10) has an average value of 5.19, with a minimum of 1.81 and a maximum of 8.19. Financial Ability (C11) has an average value of 8,610.49, ranging from 1,270.65 to 34,963.31. The Waste Management indicator (C12) has an average value of 5.54, with values ranging from 1.83 to 8.18. Recycled Products (C13) has an average of 54.74, with a minimum of 42.55 and a maximum of 60.47. Information Sharing (C14) has an average of 5.82, with values ranging from 3.84 to 9.16. Information Security (C15) has an average value of 5.18, ranging from 1.82 to 9.18. Finally, Business Intelligence (C16) has an average value of 7.27, with a range of 4.81 to 10.18, and Smart Production (C17) has an average value of 6.09, ranging from 3.86 to 8.14. This statistical analysis provides a comprehensive overview of the characteristics and behaviors of suppliers across different time periods and can serve as a foundation for comparing and evaluating their performance.

5 Result

5.1 Weighting criteria with stochastic BWM

In this section, the weights of the criteria are calculated in proportion to the SBWM method. For evaluating the criteria, three scenarios are considered: optimistic (high demand), probable (normal societal conditions), and pessimistic (demand reduction), with probabilities of 25%, 50%, and 25%, respectively. Experts in three groups of five individuals each have contributed to the evaluation of the criteria, and their weights are presented in Table 9. Based on the outputs of Table 9, it can be observed that leagile is the most important dimension, followed by circular economy, resilience, and industry 4.0. Among the criteria, recycled product, financial ability, and delivery speed are the most significant ones.

Furthermore, Table 10 displays the consistency rates (CR) of the evaluations, all of which are less than 0.1, indicating the reliability of the data in this section.

5.2 Supplier performance labeling with stochastic VIKOR

To construct a predictive model for supplier performance using machine learning algorithms, their past data must be labeled. For labeling the data, the Stochastic VIKOR approach has been utilized, which is developed for the first time in the supplier selection problem. In this approach, different values are assigned to suppliers based on various scenarios and the probability of each scenario's occurrence. The evaluation and labeling are then performed accordingly. These scenarios, similar to the SBWM section, have the same probabilities of occurrence, and the data corresponding to each scenario is selected from the relevant time interval. The tables related to the input data, as well as the steps of the stochastic VIKOR method, are reported in the Appendix. The method for determining labels for suppliers is based on the Q value of the suppliers. If the Q value is less than 0.35, the supplier is labeled as highly efficient. If the Q value falls between 0.35 and 0.7, it is efficient, and if the Q value exceeds 0.7, it is labeled as inefficient. According to the explanations provided in Table 11, the efficiency labels of the suppliers are indicated.

5.3 Supplier performance prediction model with ANNG

This section delineates the development of a predictive model for supplier performance leveraging artificial neural network (ANN) algorithms, enhanced through optimization with the Genetic Algorithm (GA). A total of 720 data records were used for model development, with 540 records allocated for model building and training data. The architecture of the ANNG model and the optimized parameters in the input and output layers are described as follows:

- Input layer: The number of neurons is equal to the number of input features (supplier evaluation indicators), which is 17 neurons.
- Hidden layers: The network comprises three hidden layers. The first layer has 150 neurons, the second layer has 100 neurons, and the third layer has 50 neurons. The number of hidden layers and neurons directly affects the model's learning capacity and complexity. More layers and neurons allow the model to learn more complex patterns. However, too many neurons can lead to overfitting. The chosen architecture was selected as the optimal amount after considering various configurations in the ANNG algorithm. The ReLU (Rectified Linear Unit) activation function is used.
- Output layer: The number of neurons in this layer is three, representing an efficient supplier that is selected, an inefficient supplier that is placed on the reserve list, and an inefficient supplier that is rejected.
- Epochs: The number of training cycles used by the neural network to adjust weights and biases. This parameter is set to 220 in this model, allowing the model to train sufficiently to learn the fundamental patterns in the data.
- Batch size: The number of samples processed simultaneously during training. A batch size of 32 is used in this model, typically chosen for a balance between memory requirements and training speed.
- Loss function: The Categorical Cross-Entropy (Softmax Cross-Entropy) loss function is chosen for this multi-class classification problem, where the goal is to predict one class out of many possible classes. The output of the neural network in this case is a vector where each element represents the probability of the input belonging to a particular class. The Softmax function is used to normalize the outputs into probabilities.
- Optimizer: The Adam optimizer is used for weight updates, chosen for its speed and efficiency in converging. Adam was selected in this study for its high speed and efficiency in updating weights.

One of the crucial parameters in ANNG is the learning rate, which was optimized using a genetic algorithm in this study. The GA steps for optimizing the learning rate in the ANNG algorithm include the following:

1. Initialization: In this step, an initial population of individuals is created. Each individual represents a set of parameters, including the learning rate, the number

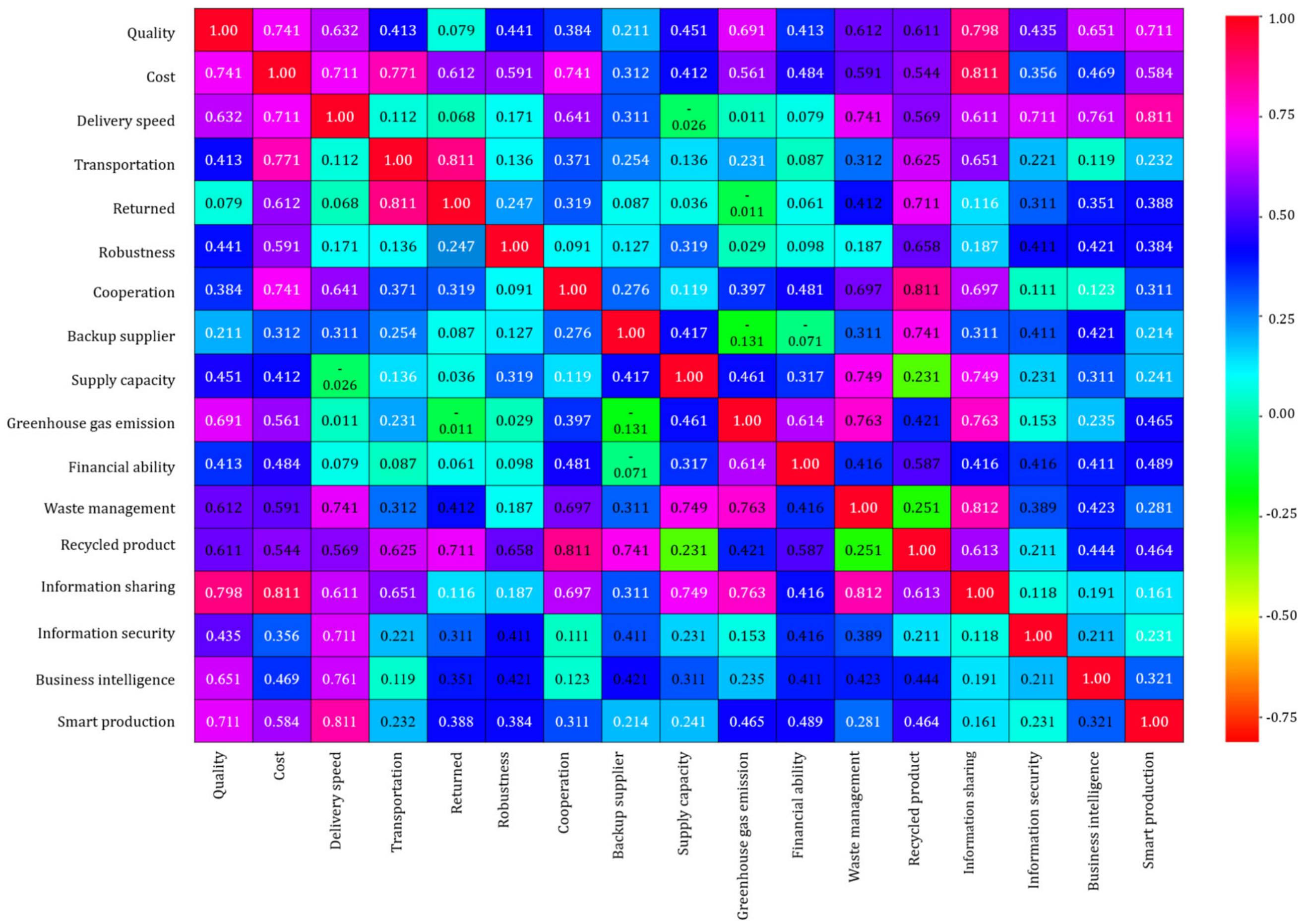
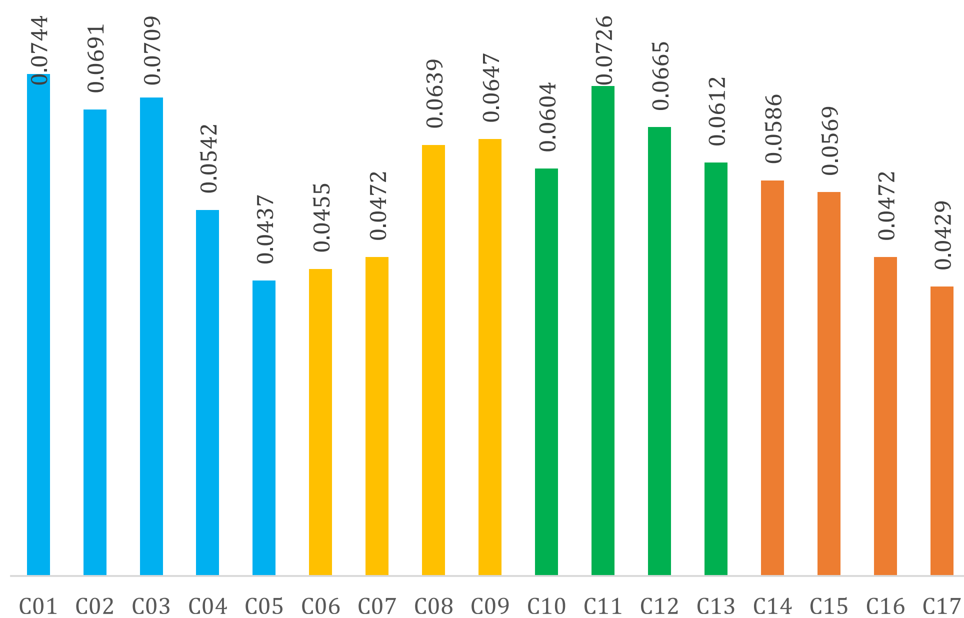


Fig. 4 Heat map of Pearson correlation between criteria

Fig. 5 The importance of criteria in predicting suppliers' performance



of neurons in each hidden layer, and the number of hidden layers. Initially, these parameters are randomly chosen within certain ranges to ensure sufficient diversity in the initial population.

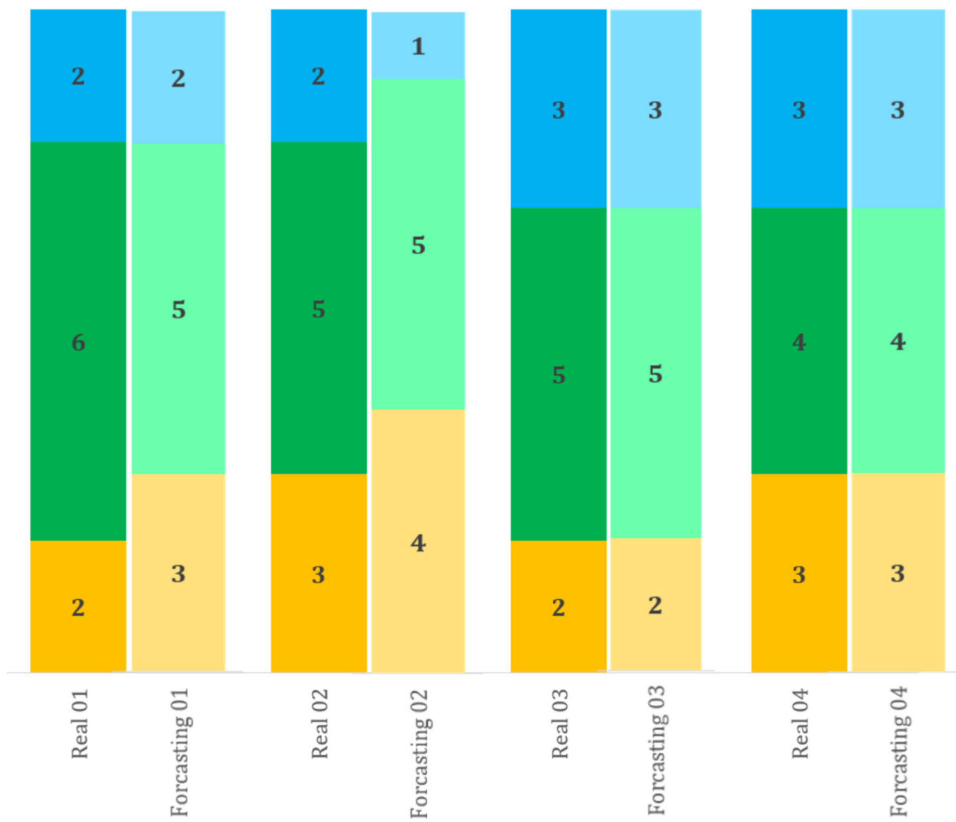


Fig. 6 Comparison of prediction results and real state

Table 12 Evaluating suppliers through various methodologies

	Stochastic VIKOR	Fuzzy TOPSIS	Fuzzy VIKOR	VIKOR
S1	6	6	6	6
S2	8	7	8	8
S3	5	5	5	5
S4	3	3	3	3
S5	7	8	9	7
S6	2	2	2	2
S7	9	10	7	9
S8	1	1	1	1
S9	10	9	10	10
S10	4	4	4	4

2. Evaluation: Each individual is used to create and train an ANNG model using its parameters. The resulting accuracy is used as the fitness score of that individual.
3. Selection: Individuals with higher fitness scores are more likely to be selected as parents. This model uses the Roulette Wheel Selection method for choosing parents. The selected parents then combine their parameters to form the next generation.
4. Crossover: Crossover is the process where two parents combine to produce offspring with mixed parameters. In this study's hybrid algorithm, a parent with a learning rate of 0.001 combined with a parent with a learning rate of 0.005 could produce offspring with a learning rate of 0.003. The goal of crossover is to combine desirable traits from different parents to improve offspring performance.
5. Mutation: Mutation introduces a small random change in the offspring's parameter, which helps maintain diversity in the population and prevents the algorithm from getting stuck in local minima.
6. Next Generation Selection: From the parents and offspring, the individuals with the best fitness scores are selected to form the next generation. This process continues until stopping criteria, such as a specified number of generations or achieving a desired accuracy, are met.

These steps are iteratively repeated, with each generation helping to further optimize the model parameters until the best-performing set of parameters is found. Overall, the objective function in this combined model is accuracy-based. In this approach, the accuracy of the model on the validation dataset is used as the evaluation criterion. The higher the model's accuracy, the more optimal the learning rate. Ultimately, after implementing the stated hybrid algorithm, the learning rate used in this study has been set at 0.0019.

Table 13 Comparison of the performance of the ANNG algorithm with other algorithms

Algorithm	Accuracy	Recall	Prec	F1-score
ANNG	0.9823	0.9723	0.9881	0.9854
ANN	0.9553	0.9443	0.9514	0.9584
SVM	0.9232	0.9123	0.9023	0.9132

In developing the predictive model via the ANNG methodology, the initial step involves examining the correlation among indicators and, more critically, assessing the influence of these indicators on supplier performance, utilizing data through Pearson correlation analysis. Figure 4 displays the Pearson correlation matrix for the indicators. Additionally, Fig. 5 highlights the significance of various indicators in the prediction of supplier performance. It is evident that quality, delivery speed, and financial capability stand out as the most crucial indicators, aligning closely with expert insights presented in the SBWM section in numerous instances.

In order to develop the model, data related to 10 suppliers were available in a period of 72 months, and a total of 720 data records were used for training and testing the model. The dataset structure is such that, for each supplier data record in each row, the values related to supplier evaluation indicators are included. Each supplier data record has 17 columns for evaluation indicator values and one label column, which is determined for each supplier using the SVIKOR method. 75% of data (540 records) were separated for model training and 25% of data (180 records) were separated for model testing. The optimized neural network algorithm was implemented with the genetic algorithm, whose findings were compared for testing with the actual values that are optimal according to the managers of the organization. In other words, the prediction of the designed model was compared with the evaluation of the organization's managers from the existing suppliers, and the results show that in many cases, it has a correct prediction with 100% accuracy, and the overall accuracy of the model is 98% on average. In fact, the designed model correctly predicts the performance of suppliers with 98% accuracy. For example, for four periods, the comparison of forecast and actual conditions is shown in Fig. 6.

5.4 Performance comparison of stochastic VIKOR

One of the methods developed in this article for the first time is Stochastic VIKOR. In order to check the effectiveness of this method, a comparison between this method and other multi-criteria decision-making methods that have been proven in the past is used. The example of evaluation and ranking of sample projects that was discussed in Sect. 2–5, in this section, it is compared with the methods of fuzzy VIKOR, VIKOR and fuzzy TOPSIS, which are shown in Table 12 of the outputs.

The outputs demonstrate that the Stochastic VIKOR method has performed comparably to many other methods in rankings, indicating its accurate performance. In other words, the SVIKOR approach has a sound logic in ranking, where in the test data, the ranking of options has a very high similarity to one another, with the only difference being in the Fuzzy TOPSIS method in one instance. This difference between Fuzzy TOPSIS and other VIKOR methods exists as well. Therefore, SVIKOR has a logic similar to the VIKOR structure but with the added capability of defining an unlimited number of scenarios. Consequently, it can consider more aspects in evaluations. Furthermore, a notable point is that this method has advantages over other approaches due to its capability and versatility in defining various scenarios with different values. This aspect leads to a more realistic and efficient performance of SVIKOR.

5.5 Analyzing the performance of the ANNG algorithm

To assess the effectiveness of the ANNG model, key metrics such as accuracy, precision, recall, and F1-score are employed to calculate the model's overall accuracy (Sazvar et al 2022).

$$Accuracy = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FP_i} \tag{16}$$

$$Precision = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FN_i} \tag{17}$$

$$Recall = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FP_i} \tag{18}$$

$$F1 - score = \frac{2 * (precision * recall)}{(precision + recall)} \tag{19}$$

where:

- True positive (TP_i): If the data actually has a P_i label and the predicted value shows the same.
- False positive (FP_i): If the individual does not have a P_i label, but the prediction result displays another label.

In order to check the efficiency and accuracy of this model, other classification models such as artificial neural network (ANN) and support vector machine (SVM) were performed on the training and test data, which are shown in Table 13 of the accuracy output of the models.

It can be observed that the ANNG algorithm has demonstrated the best efficiency and output compared to other algorithms. ANNG demonstrates the best performance due to the use of a genetic algorithm for optimizing the model's parameters. This optimization has enabled the model to learn more effectively and achieve a better balance between precision and recall, resulting in an overall improvement across all metrics. This highlights the power and importance of parameter optimization in machine learning models.

6 Discussion and conclusion

This article proposes a novel data-driven stochastic approach for evaluating and selecting suppliers with a forward-looking perspective. In this regard, the Stochastic VIKOR method has been developed, which incorporates the consideration of various scenarios in evaluations. In a previous study Nayeri et al., (2023a, b), the stochastic approach was applied and combined with multi-criteria decision-making methods for the BWM approach, showing promising results. In the present study, the stochastic nature is integrated into the VIKOR method. Based on SVIKOR and considering different demand scenarios, the efficiency labels of suppliers are determined using their past data. Subsequently, the Artificial Neural Network (ANN) algorithm is optimized using the genetic algorithm (GA) to enhance the model's accuracy and performance. Previous research Satrio et al., (2019) has been conducted on the development of the ANN algorithm based on the Genetic Algorithm, but this current paper is the first to focus on the evolution of the learning rate using the Genetic Algorithm in supplier selection. The developed algorithm outperforms other algorithms, leading to more accurate evaluations and predictions of supplier performance. In the study by Sazvar et al. (2022), hybrid data-driven models were also used for supplier evaluation; however, their models were based on fuzzy systems and did not account for different scenarios, which is an advantage of the present study as it considers various scenarios. Similarly, Zeynali et al. (2024) employed data-driven methods for supplier evaluation, where ensemble algorithms demonstrated superior performance. In the present study, the optimization of the learning rate has enhanced the accuracy and output of the neural network algorithm.

Additionally, the evaluation criteria in this study are based on the leagile, resilience, circular economy, and industry 4.0 paradigms. The studied industry is the home appliances sector, where speed, quality, and cost are highly emphasized, making the leagile paradigm relevant. Moreover, the resilience criterion gains importance due to the renewed focus on risk and crisis management in supply chains, evident in events like COVID-19 and various conflicts. As the concept of sustainable development gains prominence in supply chain contexts, the idea of a circular economy has drawn researchers' attention. Instead of sustainability, the study adopts the notion of circular economy, emphasizing its developmental aspect. Furthermore, in the current era of the fourth industrial revolution, attention to its components and criteria becomes crucial, leading to the inclusion of the industry 4.0 paradigm in the study. Studies like Rostami et al., (2023) have explored the evaluation of suppliers in alignment with the sustainable supply chain paradigms. Due to the increasing relevance of Circular economy alongside sustainability, this paradigm is considered alongside the robustness of supply chains in this paper.

Overall, this paper presents a hybrid data-driven approach that evaluates supplier performance based on documented data and expert opinions, simultaneously considering the crucial paradigms of the circular economy, industry 4.0, resilience, and agility. For instance, Khan et al. (2023) assessed resilient and sustainable suppliers using machine learning approaches, where their study utilized labeled data and presented a classification model for evaluation. The current study has developed an approach that creates a structure to transform unlabeled data into labeled data and also considers additional features in model construction. Similarly, in the study by Ali et al. (2023), a decision support system based on the random forest algorithm was developed using a labeled dataset. Therefore, in comparison to their model, the current study offers more flexibility in working with various and unlabeled data and considers a greater number of indicators and features in evaluating suppliers.

Given the discussions and the importance of themes such as the Circular Economy, Industry 4.0, resilience, agility, and responsiveness in the contemporary context, it becomes apparent that modern supply chains are increasingly characterized by their integrative nature. Consequently, it is recommended that scholars consistently incorporate hybrid paradigms in both the conceptualization of supply chains and the evaluation of suppliers. The emphasis on Industry 4.0 standards has become essential across various sectors, underscoring the importance of incorporating these criteria in considerations surrounding supply chain network design and supplier assessment. In this research, which zeroes in on the household appliances sector, Circular Economy and Leagile principles emerge as paramount in supplier evaluation, bearing comparable significance. Among the seventeen scrutinized indicators, the recycled product, financial stability, and delivery speed are highlighted as paramount, showcasing the importance of recycling initiatives, economic resilience, and operational agility.

Another noteworthy point is that given the extensive uncertainties present in the volume of data generated within supply chains, the use of hybrid approaches that incorporate human oversight of the findings is important. Furthermore, the application of scenario-based methods also contributes to increasing the accuracy of the model by considering various influential components of the problem. In this regard, it is recommended that managers and researchers utilize hybrid data-driven methods to enhance the precision of their models. Additionally, this paper suggests that the topic of order allocation could also be integrated into supplier evaluation by simultaneously considering the aspects of leagility, resilience, the circular economy, and Industry 4.0. Based on this, supply chain network models can be developed that address uncertainties through data-driven approaches. Furthermore, adding components such as customer orientation and responsiveness to the points discussed in this study introduces new innovations in the subject of supplier evaluation and selection.

Appendix

Stochastic VIKOR results

Tables 14, 15, 16, and 17 are related to Sect. 5.2 of the article. Tables 14, 15, 16, and 17 pertain to decision matrices, calculations related to the f + and f− components, and subsequently, the computation of VIKOR ranking indices in the developed Stochastic VIKOR approach. Table 14 presents the decision matrix comprising supplier input data aligned with evaluation indices and delineated by scenarios. In each scenario, suppliers can have varying or identical values across different indices. In Table 15, the values for the f + and f− components were calculated in accordance with the formula and explained in step 4 of Sect. 3.2. Tables 16 and 17 report the calculations from step 5 explained in Sect. 3.2, based on which the VIKOR index is computed.

Table 14 The decision matrix in evaluating sample suppliers based on scenarios

	Scenario1 C1	Scenario2	Scenario3	Scenario1 C2	Scenario2	Scenario3	Scenario1 C3	Scenario2	Scenario3
S1	8.00	10.00	9.00	122,268	122,268	122,268	9.60	12.00	10.80
S2	7.00	6.00	6.00	77,539	77,539	77,539	8.40	7.20	7.20
S3	4.00	5.00	5.00	136,877	136,877	136,877	4.80	6.00	6.00
S4	5.00	5.00	5.00	186,397	186,397	186,397	6.00	6.00	6.00
S5	6.00	6.00	6.00	90,842	90,842	90,842	7.20	7.20	7.20
S6	7.00	8.00	9.00	124,293	124,293	124,293	8.40	9.60	10.80
S7	8.00	8.00	8.00	39,828	39,828	39,828	9.60	9.60	9.60
S8	8.00	8.00	8.00	202,564	202,564	202,564	9.60	9.60	9.60
S9	7.00	7.00	7.00	51,538	51,538	51,538	8.40	8.40	8.40
S10	6.00	5.00	4.00	152,209	152,209	152,209	7.20	6.00	4.80
	C4			C5			C6		
S1	20.51	25.64	23.08	0.91	0.92	0.94	2170.18	2170.18	2170.18
S2	17.95	15.38	15.38	0.85	0.84	0.89	1376.26	1376.26	1376.26
S3	10.26	12.82	12.82	0.86	0.84	0.86	2429.48	2429.48	2429.48
S4	12.82	12.82	12.82	0.76	0.79	0.81	3308.44	3308.44	3308.44
S5	15.38	15.38	15.38	0.90	0.84	0.85	1612.38	1612.38	1612.38
S6	17.95	20.51	23.08	0.85	0.84	0.89	2206.12	2206.12	2206.12
S7	20.51	20.51	20.51	0.86	0.84	0.86	706.92	706.92	706.92
S8	20.51	20.51	20.51	0.79	0.78	0.68	3595.38	3595.38	3595.38
S9	17.95	17.95	17.95	0.79	0.86	0.84	914.77	914.77	914.77
S10	15.38	12.82	10.26	0.81	0.82	0.83	2701.61	2701.61	2701.61
	C7			C8			C9		
S1	658.13	658.13	658.13	1.00	1.00	1.00	195.00	195.00	195.00
S2	781.30	781.30	781.30	5.00	5.00	5.00	312.00	312.00	312.00
S3	2025.00	2025.00	2025.00	6.00	6.00	6.00	540.00	540.00	540.00
S4	3769.60	3769.60	3769.60	10.00	10.00	10.00	729.60	729.60	729.60
S5	495.60	495.60	495.60	3.00	3.00	3.00	201.60	201.60	201.60

Table 14 (continued)

	C7			C8			C9		
S6	1380.00	1380.00	1380.00	4.00	4.00	4.00	414.00	414.00	414.00
S7	715.00	715.00	715.00	4.00	4.00	4.00	660.00	660.00	660.00
S8	1680.00	1680.00	1680.00	5.00	5.00	5.00	268.80	268.80	268.80
S9	563.50	563.50	563.50	4.00	4.00	4.00	386.40	386.40	386.40
S10	4725.00	4725.00	4725.00	10.00	10.00	10.00	1080.00	1080.00	1080.00

	C10			C11			C12		
S1	7.00	7.00	7.00	6255.33	6255.33	6255.33	5.00	5.00	5.00
S2	6.00	6.00	6.00	3966.94	3966.94	3966.94	5.00	5.00	5.00
S3	8.00	8.00	8.00	7002.72	7002.72	7002.72	8.00	8.00	8.00
S4	6.00	6.00	6.00	9536.23	9536.23	9536.23	8.00	8.00	8.00
S5	4.00	4.00	4.00	4647.53	4647.53	4647.53	4.00	4.00	4.00
S6	6.00	6.00	6.00	6358.92	6358.92	6358.92	6.00	6.00	6.00
S7	4.00	4.00	4.00	2037.63	2037.63	2037.63	5.00	5.00	5.00
S8	2.00	2.00	2.00	10,363.33	10,363.33	10,363.33	4.00	4.00	4.00
S9	2.00	2.00	2.00	2636.73	2636.73	2636.73	2.00	2.00	2.00
S10	7.00	7.00	7.00	7787.12	7787.12	7787.12	7.00	7.00	7.00

	C13			C14			C15		
S1	40.00	49.00	52.00	4.00	5.00	5.00	2.00	2.00	2.00
S2	60.00	41.00	49.00	6.00	6.00	6.00	5.00	5.00	5.00
S3	59.00	57.00	48.00	6.00	6.00	6.00	5.00	5.00	5.00
S4	47.00	57.00	54.00	9.00	9.00	9.00	9.00	9.00	9.00
S5	53.00	46.00	44.00	5.00	5.00	5.00	5.00	5.00	5.00
S6	46.00	43.00	45.00	5.00	5.00	5.00	5.00	5.00	5.00
S7	55.00	47.00	46.00	5.00	5.00	5.00	4.00	4.00	4.00
S8	48.00	41.00	57.00	4.00	4.00	4.00	5.00	5.00	5.00
S9	44.00	45.00	55.00	5.00	5.00	5.00	4.00	4.00	4.00
S10	43.00	52.00	40.00	9.00	9.00	9.00	8.00	8.00	8.00

	C16			C17		
S1	6.00	6.00	7.00	5.00	7.00	4.00
S2	5.00	8.00	10.00	6.00	8.00	4.00
S3	10.00	9.00	7.00	8.00	5.00	5.00
S4	5.00	8.00	9.00	7.00	8.00	7.00
S5	10.00	7.00	5.00	6.00	8.00	6.00
S6	9.00	7.00	5.00	6.00	6.00	6.00
S7	7.00	6.00	8.00	5.00	7.00	4.00
S8	9.00	6.00	7.00	4.00	4.00	4.00
S9	8.00	7.00	9.00	8.00	7.00	5.00
S10	10.00	6.00	6.00	7.00	4.00	7.00

Table 15 f + and f- values in the scenario

	Scenario1	Scenario2	Scenario3	Scenario1	Scenario2	Scenario3	Scenario1	Scenario2	Scenario3
	C1			C2			C3		
f^+	0.001070	0.004396	0.002847	0.002994	0.009979	0.006985	0.001114	0.004576	0.002964
f^-	0.000535	0.002198	0.001265	0.000179	0.000596	0.000417	0.000557	0.002288	0.001317
	C4			C5			C6		
f^+	0.000791	0.003252	0.002106	0.000087	0.000290	0.000207	0.002819	0.009395	0.006577
f^-	0.000396	0.001626	0.000936	0.000068	0.000231	0.000145	0.000168	0.000561	0.000393
	C7			C8			C9		
f^+	0.003119	0.010397	0.007278	0.001655	0.005516	0.003861	0.001839	0.006129	0.004290
f^-	0.000143	0.000477	0.000334	0.000165	0.000552	0.000386	0.000332	0.001107	0.000775
	C10			C11			C12		
f^+	0.001292	0.004305	0.003014	0.003766	0.012552	0.008787	0.001350	0.004500	0.003150
f^-	0.000323	0.001076	0.000753	0.000225	0.000749	0.000525	0.000338	0.001125	0.000788
	C13			C14			C15		
f^+	0.001199	0.003998	0.002763	0.001081	0.003602	0.002522	0.001250	0.004165	0.002916
f^-	0.000800	0.002732	0.001939	0.000480	0.001601	0.001121	0.000278	0.000926	0.000648

	C16			C17		
f^+	0.001419	0.004730	0.003311	0.001075	0.003583	0.002194
f^-	0.000710	0.002838	0.001656	0.000537	0.001791	0.001254

Table 16 Utility values of plans

	Ljs			SSj
S1	11.092	10.186	10.054	10.37947
S2	10.041	11.820	10.766	11.11201
S3	9.187	10.471	10.189	10.0797
S4	8.860	8.318	7.039	8.133951
S5	10.914	12.818	12.543	12.27336
S6	9.689	11.012	9.283	10.24902
S7	9.925	11.635	10.827	11.00554
S8	10.474	13.017	11.017	11.88136
S9	11.709	13.092	11.535	12.35676
S10	6.890	9.749	8.811	8.799775

Table 17 The regret values of the plans

	Tjs			Rj
S1	1	1	1	1
S2	0.972255132	1	0.972255132	0.986128
S3	1	1	0.851477072	0.962869
S4	1	1	0.8	0.95
S5	1	1	1	1
S6	0.914114242	0.914114242	0.914114242	0.914114
S7	1	1	1	1
S8	1	1	1	1
S9	1	1	1	1
S10	0.85	1	1	0.9625

Author contributions Bahar and Mohammad conceived of the presented idea. Bahar and Mohssen developed the theory and performed the computations. Amirreza verified the analytical methods. All authors discussed the results and contributed to the final manuscript. Bahar and Mohammad carried out the experiment. Bahar wrote the manuscript with support from Mohssen.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability The data that support the findings of this article are available from the corresponding author, M. Sheikhalishahi upon request.

Declarations

Conflict of interest The authors have no conflict of interests to disclose.

Ethical approval This material is the authors' own original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner. The paper properly credits the meaningful contributions of co-authors and co-researchers. The results are appropriately placed in the context of prior and existing research. All sources used are properly disclosed. All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

Consent to participate N/A.

Consent to publish N/A.

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