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Green Supplier Evaluation and Selection in the Manufacturing Industry Using the Taguchi-VIKOR Methods

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ABSTRACT

This paper proposes three methods for the joint optimization and selection of parameters in controlling the exhaust emission from logistics and packing industries, using the Taguchi-VIKOR, Taguchi-Pareto-VIKOR, and Taguchi-ABC-VIKOR methods. From the delta values of the Taguchi method, parameters F, E, A, B, C, and D were placed 1st, 2nd, 3rd, 4th, 5th, and 6th with delta values of 59.0066, 7.5263, 7.5261, 0.1150, 0.1113 and 0.1107, respectively. The delta ratio, delta variability, mean delta value and median delta value are 58.8959, 12.3993, and 3.8206, respectively. Furthermore, the optimal parametric setting is $A_1B_1C_1D_1E_1F_1$, which means 52 million dollars for revenue, 127 billion packing units, 0.77 optimal growth rate, 1.5 units of materials, 5581 kilotons of quantity consumed and 1 unit of carbon dioxide equivalent of packing materials. The methods are the cornerstone for evaluating the high-performing packing factor associated with greenhouse gas emissions and concurrently obtaining optimized values for packing enterprises to reduce emissions. Besides, and differently from earlier studies, methods such as Pareto, ABC, and VIKOR differentiate the alternative coupled Taguchi methods proposed in the literature. In addition, the following novel elements of the Taguchi method are introduced: Delta ratio, delta variability, mean delta value, delta/HOPV, delta/LOPV, and delta/AOPV. The results suggest that the developed methods adequately represent the optimized values and ranks obtained using the field data set from literature.

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1. INTRODUCTION

World-class and aspiring world-class manufacturers strive to maintain high levels of reprobation by operating within the guidelines of Industry 4.0 Environment that stipulate low carbon emissions and environment protection. Within the Industry 4.0 Environment context, it is appreciated that tangible goods and services needed for production in manufacturing plants are supplied through complicated and long international supply chains. Goods are packaged from their manufacturing sites and transported to us through chains of trucks, ships, trains, delivering vehicles, and distribution hubs. The critical issue here is that these delivery facilities burn fossil fuels that are associated with health and environmental influences. A significant impact of carbon emissions from fossil fuels is climate change, a condition that nature strives to survive while competing for the oxygen available in the air, which is being used up by the carbon emissions produced during the transportation of these goods. Apart from the transportation system for the distribution of goods, which produces carbon emissions, even within the manufacturing plant, electricity and heating have been found to produce carbon emissions and power plants too. However, it has been argued that the greatest CO_2 emission is traced to fossil fuel combustion that is present in vehicles. Experts describe the damage caused by fossil fuel combustion as overwhelming such as climate change.

From the above discussion, deviations from Industry 4.0 Environment principal drivers are the increasing cause of industrial accidents motivated by environmental concerns. However, adherence to these Industry 4.0 Environmental norms and guidelines are critical issues to maintaining a healthy environment and conserving resources and company funds. Unfortunately, it is estimated in the literature that freight accounts for roughly 30% of all transport-associated carbon emissions. This includes freight due to ships, trains, and trucks. This 30% value is what is given into that atmosphere every year. As these carbons are emitted into the atmosphere, the pollution of air in cities is responsible for tens of thousands of premature deaths yearly.

Attempts to reduce this environmental impact are the suggestion to introduce shorter and more straightforward supply chains. This implies that customers should buy goods near them. This suggestion may not work in a situation where there are constraints of land, labor, and capital by prospector manufacturers willing to site their companies near us. It means that alternative approaches should be used to reduce pollution from complicated and long supply chains and these approaches have practical appeals. A worldwide accepted approach is the Home Depot adopted strategy, in which enhanced efficiency and minimized costs in a supply chain are experienced. Overall, when the reduction in energy consumption and emissions is considered there is a huge success. Unfortunately, the Home Depot strategy is localized to the United States and China relationship and may not be easily adaptable to other parts of the world as it has huge activities and the commitment of several stakeholders involved. Also, there is a paucity of evaluation schemes contemplating greener transportation performance to evaluate and manage suppliers that transport products to consumers using supply vehicles such as trucks and lorries with loaded products from the manufacturing company to the consumers. Therefore, an analytical approach may be a viable alternative to solve this problem. By establishing indices associated with green supplies, this work established a new structure with an assessment index scheme that reflects the operational status of the supplier through vehicles. The versions of the Taguchi method were hybridized with the VIKOR method to establish a selection process for the parameters considered in the system. A case examination from a packing industry whose field data was obtained from the literature was employed to demonstrate the effectiveness of the processed structure.

In the company studied, there is recent but high attention given to green practices by all the drivers. There are concerns raised about the high anti-green supply activities of all the company's supply (delivery) trucks and lorries while directing attention to the emissions given out by the trucks used for deliveries. The company has various grades of lorries for deliveries. The company uses emissions from such vehicles to control and monitor the amount of green activity contributions to the environment. It is observed that the topic of vehicle emission within the packing industry using multi-response optimization methods integrating Taguchi methods and VIKOR approach has been explored in recent years and therefore, this gap compels researchers to conduct new research, which is required to fill the gap. Although the Taguchi-VIKOR methods have been used in engineering research, in particular, the field of manufacturing which welcomes such methods is indirectly related to the logistics and supply chain areas of research. This validates the topic of the Taguchi-VIKOR method being re-examined, providing new information.

Given the gaps pointed out by the literature review conducted in this study, the main objective of this research is to develop and implement three integrated multicriteria optimization tools and compare them with an alternative method. Thus, the objective of this study is to assess and select the best parameters in the green supply chain using the Taguchi-VIKOR, Taguchi-Pareto-VIKOR, and Taguchi-ABC-VIKOR methods. The amalgamation of VIKOR with any of the Taguchi methodical variants mentioned encompasses the introduction of an adjusted normalization scheme for the implementation of the CRITIC method. Initially, the number of factors may be different from the number of levels and the difference is the number of rows introduced, with zero entry matrix to form a square matrix for the evaluation of the measure of conflict of the matrix. The novelty of the present study lies in the clear, logical structure and detailed description of the integrated method (methodological innovations), the introduction of new analytical metrics, and the targeted industrial application to vehicle emissions in the packing industry. Additionally, the novelty of this article is in its alignment with contemporary environmental and sustainability goals. By combining well-established methods in a novel way and introducing new metrics for analysis this research makes a significant novel contribution to the fields of industrial engineering and Engineering management. Moreover, the finding's practical relevance and real-world applicability further enhance the study's originality and impact.

2. LITERATURE REVIEW

2.1. Multicriteria decision-making method in supplier evaluation

Bai and Sarkis (2010) employed rough-set theories to associate some supply chain parameters. Buyukozhan and Cifci (2012) analyzed GSC management and its capacity features using a hybrid of fuzzy Decision Trial and Evaluation Laboratory Model, Analytical Network Process, and Technique for Order Performance by Similarity to Ideal Solution. Fu et al. (2012) assessed the associations across some supply chain systems. Shen et al. (2013) utilized fuzzy set theory to convert ambiguous human perceptions into a performance score for suppliers. Dobos and Vorosmarty (2014) analyzed vendor evaluation methods to incorporate environmental and green concerns. Dou et al. (2014) used a grey analytical network process-based method to develop green supplier programs. Akman (2015) established performance attributes for evaluating green suppliers by using factor analysis and the VIKOR method. Govindan et al. (2015) reviewed the literature on green supplier selection published from 1997 to 2011. Ghorabaee et al. (2016) established a new weighted aggregated sum product assessment method for supplier ranking. Mousakhani et al. (2017) analyzed group decision-making strategies to select green suppliers. Chatterjee et al. (2018) proposed a multi-criteria evaluation framework for selecting green suppliers. Demir et al. (2018) established the VIKOR-based green supplier sorting methodology to evaluate suppliers' environmental performance. Lo et al. (2018) integrated the best-worst, improved fuzzy approach for order preference by similarity to ideal solution, and fuzzy multi-objective linear programming methods for supplier evaluation.

dos Santos et al. (2019) evaluated green suppliers for the furniture sector. Liou et al. (2019) obtained a data-driven method that used rules/patterns from historical data. Gao et al. (2020) suggested a framework for group consensus decision-making to assist in selecting the best green supplier for the manufacture of electronics. Gao et al. (2021) suggest a novel method that integrates the cloud model and decision-making trial and evaluation laboratory to establish the key causal factors for the assessment of green suppliers using qualitative heterogeneous judgments. Liou et al. (2021) suggest a novel hybrid multiple criteria decision making (MCDM) model that combines the support vector machine (SVM), fuzzy best-worst method, and fuzzy technique for order preference by similarity to ideal solution techniques. Goodarzi et al. (2022) presented a joint method based on multicriteria and multiobjective schemes to select the best green suppliers and allocate orders under uncertainty using the TOPSIS and Gray Correlation methods.

Masoomi et al. (2022) evaluated a group of strategic suppliers based on their green capabilities through the joint Complex Proportional Assessment of Alternatives and Weighted Cumulative Sum-Product Evaluation methods with the fuzzy best-worst method. Wu and Liao (2023) used a geometric language scale to tackle supply chain problems. Yang and Jiang (2023) studied the impact of consumers' environmental orientation on their green innovation and the influencing role of suppliers' key slack resources. Norheim-Hansen (2023) analyzed how to prioritize suppliers for the growth of green suppliers. Sonar et al. (2022) developed the hierarchical relationship between the criteria and identified key factors for supplier selection. Zhang et al. (2022) used a systems dynamics approach to analyze the electricity supplier's involvement. Bodendorf et al. (2022) presented a macro approach to sustainable supplier analysis.

Sharafi et al. (2022) presented a fuzzy Data Envelopment Analysis model for selecting green suppliers through the gathering of expert opinions. Sarkar et al. (2022) improved the greening efforts of a product that moves through a two-level supply chain by using the joint economic lot size model. Feng and Gong (2020) suggested a method for the choice of suppliers using a joint linguistic entropy weight approach with a multi-objective scheme.

2.2. Green supplier evaluation and selection in the manufacturing industry

Lo (2023) presented a broad assessment framework of sustainable suppliers within the Industry 5.0 era. The approach used is an integration of three methods; critique, adjusted classifiable TOPSIS, and variable precision-dominance-oriented roughest method. The author presented results that show that TOPSIS can be used for assessing the rating of new alternative suppliers. Jefroudi and Darestani (2024) presented the results of the fuzzy best-worst method (BWM) which showed that the top most important was customer contentment, a committed relation, and restriction of any form of pollution, among the 13 standards considered. TOPSIS chose supplier 3 as top top-ranked supplier, 3 as top top-ranked supplier, with supplier 6 coming behind supplier 3 and then supplier 1. Acar et al. (2024) presented new findings, which revealed that Evidential F-MCDM and integrating multiple regression are capable of being a hybrid method in choosing of account supplier with these findings, a different view is taken into account in the green supplier selection decision-making process by considering the impacts of criteria in the MCDM model on green performance. This revolution helps in enhancing the selection process and determination of criteria in MCDM approaches. Furthermore, green dynamic capability is the most critical criterion in the supplier section based on their green performance in the scope of this investigation.

Azizi et al. (2024) showed that the smart TOPSIS method improves decision precision and reduces computational intricacy this then makes it a tool that can be used for other applications, even if its primary role is the green supplier section, it can also be applied in the real world in other research fields. Bokesht et al. (2023)

presented a study whose target is to provide food business packaging operations with a novel GSS application methodology. The most used criteria were determined by a literature review and used to create a new criteria state. The new criteria set was then used with Pythagoran's fuzzy technique for order preference by similarity to ideal solution (PF-TOPSIS) methods to choose the best supplier. Linguistic expression was used by a group of three experts to evaluate the five alternatives. Lastly, a sensitivity analysis was done, comparing the results with the classical TOPSIS method, this research shows that the proposed approach was productive. Kara et al. (2024) proposed a supplier selection method incorporating green issues in the performance assessment. Two methods were used. The first is the multiple regression method while the second is the Demester-Shafer theory-oriented evidential multicriteria decision-making method. The application of the method was made in supplier selection within the automotive industry. Nafei et al. (2024) combined the TOPSIS method with the neutrosophic triplets approach in green supplier selection within the manufacturing industry. Hajiaghaei-Keshteli et al. (2023) introduced the green supplier selection method in food business packaging operations using Pythagorean fuzzy TOPSIS to choose the best suppliers.

Haryono et al. (2024) presented a study on the hybridization of two methods, which particularly involves the combination of AHP and linear programming. It revealed that the presented approach is the most used and most effective in the supplier selection outcome in alignment with the food industry's needs. Ghadimi et al. (2024) presented a result that shows that the c-constraint optimization method leads to a higher total value of sustainable purchasing compared to the traditional max-min method. Rahman et al (2022) provided a study expected to support decision-making within emerging economic textile dyeing industries by helping them efficiently choose suppliers who are both economically viable and environmentally sustainable in the long term. Garg (2021) presented a finding that indicates that utilizing a structured decision-making technique is crucial, especially in intricate scenarios involving both qualitative and quantitative criteria.

Singh et al. (2024)used the novel Tomadu de Decisao interactive multicriteria decision making framework to choose the optimal supplier to supply criteria hydrogen fuel cell components. Güneri and Deveci (2023) presented a novel method to determine the supplier's selection in the defense industry and can also be extended to other industries.

2.3. Fuzzy VIKOR Method

Pérez-Velázquez et al. (2020) introduced a combination approach to assist decision making which relates to supplier selection of technology specifically for northeast Brazil. The VIKOR method was combined with the diffused inference approach, while the entropy method was used for weight assessment in the study. It was reported that collecting data from various sources and analyzing the input variables can assist in developing the criteria for selecting suppliers in photo voltaic module installation. Kumar and Barman (2021) used fuzzy TOPSIS as well as fuzzy VIKOR to select suppliers under the green concept for sponge and iron steel manufacturing. The method was validated with local industrial data in the eastern region of India. Datta et al. (2012) presented an assessment scheme for suppliers' environmental performance using the VIKOR method combined with a fuzzy expert system having interval-valued fuzzy numbers. A case study was reported to validate the approach. Wu et al. (2019) established a combined approach for multiple criteria group decision-making by using the type-2 fuzzy best-worst and extended VIKOR approaches. The method was used in practice for green supplier selection. Awasthi and Kannan (2016) analyzed the green supplier development program with a combined fuzzy VIKOR and nominal group technique. A numerical example was used to demonstrate the utility of the method.

3. METHODOLOGY

3.1. Taguchi method and other ratios

The Taguchi method is known to work using the mechanism of signal-to-noise ratios, which finally produce the optimal parametric settings and data values. The main and popular criterion of the signal-to-noise ratios is the larger-the-better, the smaller-the-better, and the nominal-the-best. In this work, the larger-the-better criterion (i.e. Equation (1)) and the smaller-the-better criterion (i.e. Equation (2)), are used for analysis and are represented in the section on methodology.

Larger-the-better

$$SN = -10\log \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2} \tag{1}$$

Smaller-the-better

$$SN = -10\log \frac{1}{n}\sum_{i=1}^{n} y_i^2 \tag{2}$$

From both Equations (1) and (2), on the right-hand sides of the equations, there are two main terms of interest. These are "n" which represents the number of responses obtainable from the process, and "y" which is the response obtainable at the response level. The symbol "∑" is the summation sign which aids in the iteration of the process.

For normalization of the decision matrix,

$$\overline{X}_{ij} = \frac{X_{ij} - X_{j\,worst}}{X_{j\,best} - X_{j\,worst}} \tag{3}$$

Unity measure,

$$S_i = \sum\left(w_j.\frac{X_{best} - X_{ij}}{X_{best} - X_{worst}}\right) \tag{4}$$

$$R_i = \max_j\left(w_j.\frac{X_{best} - X_{ij}}{X_{best} - X_{worst}}\right) \tag{5}$$

The fuzzy geometric mean (r_i) is obtained using Equation (6):

For each entry (l_i, m_i,u_i) in the matrix, (i = 1, 2, 3, 4, 5, 6)

$$r_i = (l_1 \times l_2 \times l_3 \times l_4 \times l_5 \times l_6)^{1/6}, (m_1 \times m_2 \times m_3 \times m_4 \times m_5 \times m_6)^{1/6}, (u_1 \times u_2 \times u_3 \times u_4 \times u_5 \times u_6)^{1/6} \tag{6}$$

3.2. Procedure to implement Taguchi-fuzzy VIKOR, Taguchi Pareto-fuzzy VIKOR, and Taguchi-ABC fuzzy VIKOR

The implementations of the above-mentioned procedure are in several phases starting with the Taguchi methodical aspect that is discussed as follows:
Phase 1: Taguchi methodical aspects. These phases consist of steps including the following:
Step 1: Translate the factors and levels of parameters into an orthogonal array and validate the proposed model using Taguchi-fuzzy. In the present perspective, validation refers to demonstrating that the innovative models of Taguchi-based VIKOR made sense. Moreover, validation of the proposed model is done as a research strategy to promote the usage of the proposed model thereby enhancing improved communication and dissemination of the present findings. In the current study, using the average signal-to-noise ratios as the basis, the fuzzy tool is applied and then the VIKOR method is used on the data. This means that the method used for validation is the Taguchi-fuzzy-VIKOR method. It is used to validate the three methods of Taguchi-VIKOR, Taguchi Pareto-VIKOR, and Taguchi ABC-VIKOR. Furthermore, Table 2 which contains the average signal-to-noise ratios referred to in Table 2 is further normalized as shown in Table 3 in addition a peer-wise comparison matrix (Table 49) is introduced. Table 5a is produced where the critic weights are introduced into the pair-wise comparison matrix for further analysis. Also, Table 6a shows the fuzzy numbers and their respective numerical values. For these numerical values that are identified as fractions, the formula used to evaluate the fuzzy number is in Equation 3.

4. RESULTS AND DISCUSSIONS

In this section, the results obtained from the application of the methods, which are comprised of Taguchi-VIKOR methods are discussed. These include topics such as Taguchi-VIKOR, Taguchi Pareto-VIKOR, and Taguchi-ABC-VIKOR methods, and are discussed in various sub-sections as follows:

4.1. Taguchi-VIKOR method

Taguchi method's outputs are the optimal parametric settings (when the experimental trials are taken on a full scale), delta values, and ranks. Taguchi-VIKOR method is a unique multi-response method, that showcases the interactions among the six inputs of the vehicle emission problem, which is discussed here. The Taguchi method is first employed and the output of the Taguchi method is used as the input to the VIKOR method. The Taguchi methodical data is extracted from Benrajesh and Rajan (2019) which provides information on factors and levels and their translations through orthogonal arrays into the delta values and optimal parametric setting aided the computations of the signal-to-noise ratios and their averages at various levels of the parametric values. The interesting analysis discussed here starts with the selection of six factors, A, B, C, D, E, and F, and the definition of levels to three scales such as levels 1, 2, and 3. Here, an L27 is regarded as a suitable orthogonal matrix and was used to analyze the signal-to-noise ratios for the process. It was decided that the smaller-the-better signal-to-noise ratio, criterion is fit for usage since the six parameters are found to be non-beneficial to the system. Consequently, Equation (2) from the methodological section is used to compute the signal-to-noise ratios while using information from the factors and levels (Table 1) and Table 2, which contains the signal-to-noise ratios.

Table 2 consists of 27 run orders with each run order containing information on the index of the orthogonal array representing the factors A to F. These indices are then read from the factor level table for the parameters to understand their transformations. It is their transformed values that are applied to Equation (2) to give the signal-to-noise ratio for each run order. Considering run order 1, there are three other sections in front of the position where the run order is located. These are the orthogonal array section, which contains parameters A to F in terms of orthogonal matrix ranging from 1 to 3 for level identification. The second section is the translated values of the orthogonal array, which was obtained from the factor-level table. The third section is for the signal-to-noise ratios. In some cases, there could be the smaller-the-better criterion used for a set of factors while the large-the-better criterion is used for another set of factors. The individual values of the signal-to-noise ratios are added to obtain a unified signal-to-noise ratio for the process. Now, concerning run order 1, the value of -82.7184 was obtained as the SNR applying Equation (2) to the field data provided by Benrajesh and Rajan (2019). To compute the average signal-to-noise ratios, each level and factor is treated separately. Consider the treatment of factor A and level 1, all the run orders having the value of 1 representing level 1 are tracked. These are nine and are distributed from run orders 1 to 9. However, the

Table 1. Input Parameters from Benrajesh and Rajan (2019)

Level	Input parameters A	B	C	D	E	F
Level 1	52*	127*	0.77*	1.5*	5581*	1*
Level 2	171	1494	16.00	2.5	43666	12300000
Level 3	287	2861	30.34	3.5	81750	24600000
Min	52	127	0.77	1.5	5581	1
Max	287	2861	30.34	3.5	81750	24600000

Key: * Optimal parametric settings; A: Revenue attained in the packing industry for a year (million dollars); B: Packing units Sold (Billion); C: Compound annual growth rate (2015); D: Materials used for packing; E: Quantity consumed in Kilo tons; F: Carbon dioxide equivalent of Packing materials

Table 2. Orthogonal array and its translation

No.	Orthogonal array						Translation						Measures		
	A	B	C	D	E	F	A	B	C	D	E	F	SNR	%	Cum %
1	1	1	1	1	1	1	52	127	0.77	1.5	5581	1	-82.71840	2.29	2.29
2	1	1	1	1	2	2	52	127	0.77	1.5	43666	12300000	-149.5797	4.14	6.42
3	1	1	1	1	3	3	52	127	0.77	1.5	81750	24600000	-155.6002	4.30	10.73
4	1	2	2	2	1	1	52	1494	16.00	2.5	5581	1	-83.01671	2.30	13.02
5	1	2	2	2	2	2	52	1494	16.00	2.5	43666	12300000	-149.5797	4.14	17.16
6	1	2	2	2	3	3	52	1494	16.00	2.5	81750	24600000	-155.6003	4.30	21.46
7	1	3	3	3	1	1	52	2861	30.34	3.5	5581	1	-83.72950	2.32	23.78
8	1	3	3	3	2	2	52	2861	30.34	3.5	43666	12300000	-149.5797	4.14	27.91
9	1	3	3	3	3	3	52	2861	30.34	3.5	81750	24600000	-155.6003	4.30	32.22
10	2	1	2	3	1	2	171	127	16.00	3.5	5581	12300000	-149.5797	4.14	36.35
11	2	1	2	3	2	3	171	127	16.00	3.5	43666	24600000	-155.6002	4.30	40.66
12	2	1	2	3	3	1	171	127	16.00	3.5	81750	1	-106.0313	2.93	43.59
13	2	2	3	1	1	2	171	1494	30.34	1.5	5581	12300000	-149.5797	4.14	47.73
14	2	2	3	1	2	3	171	1494	30.34	1.5	43666	24600000	-155.6002	4.30	52.03
15	2	2	3	1	3	1	171	1494	30.34	1.5	81750	1	-106.0327	2.93	54.96
16	2	3	1	2	1	2	171	2861	0.77	2.5	5581	12300000	-149.5796	4.14	59.10
17	2	3	1	2	2	3	171	2861	0.77	2.5	43666	24600000	-155.6002	4.30	63.40
18	2	3	1	2	3	1	171	2861	0.77	2.5	81750	1	-106.0367	2.93	66.33
19	3	1	3	2	1	3	287	127	30.34	2.5	5581	24600000	-155.6002	4.30	70.64
20	3	1	3	2	2	1	287	127	30.34	2.5	43666	1	-100.5846	2.78	73.42
21	3	1	3	2	3	2	287	127	30.34	2.5	81750	12300000	-149.5798	4.14	77.55
22	3	2	1	3	1	3	287	1494	0.77	3.5	5581	24600000	-155.6002	4.30	81.86
23	3	2	1	3	2	1	287	1494	0.77	3.5	43666	1	-100.5896	2.78	84.64
24	3	2	1	3	3	2	287	1494	0.77	3.5	81750	12300000	-149.5798	4.14	88.78
25	3	3	2	1	1	3	287	2861	16.00	1.5	5581	24600000	-155.6002	4.30	93.08
26	3	3	2	1	2	1	287	2861	16.00	1.5	43666	1	-100.6032	2.78	95.86
27	3	3	2	1	3	2	287	2861	16.00	1.5	81750	12300000	-149.5798	4.14	100

Key: A = Revenue in the packing industry, for a year (2015) -{Million dollars}; B = Packing Units sold (Billion); C = CAGR-2015; D = Packing Materials; E = Quantity consumed in Kilotons; F = CO2e of Packing materials

Table 3. Direct parameter response table (Taguchi method)

Level	A	B	C	D	E	F
1	-129.445*	-133.8749*	-133.8761*	-133.8771*	-128.4449*	-96.5936*
2	-137.0711	-133.9088	-133.9101	-133.9086	-135.2575	-149.5797
3	-135.2575	-133.9899	-133.9874	-133.9878	-137.0712	-155.6002
Delta values	7.5261	0.1150	0.1113	0.1107	7.5263	59.0066
Ranks	3	4	5	6	2	1
Best	-137.0711	-133.9899	-133.9874	-133.9878	-133.0712	-155.6002
Worst	-129.445	-133.8749	-133.8761	-133.8771	-129.4449	-96.5936

Key: *optimal parametric setting, A = Revenue in the packing industry, for a year (2015) -{Million dollars}; B = Packing Units sold (Billion); C = CAGR-2015; D = Packing Materials; E = Quantity consumed in Kilotons; F = CO2e of Packing materials

corresponding values of these run orders are monitored, which are from -.82.7184 to -155.6003 along the SNR column. The intention is to find the average of these values, which gives -129.415. To further explain, the average SNR under A1 is 1/9(-82.7184 -149.5797 -155.6002 -83.01671 -149.5797 -155.6003 -83.7295 -149.5797 -155.6003), which give a value of -129.445, the value put at the intersection of A and 1. Furthermore, A2 is calculated as the average of SNR under A2, which is 1/9(-149.5795 -155.6002 -106.0313 -149.5797 -155.6002 -106.0327 -149.5796 -155.6002 -106.0367) that give a value of -137.0711 at the intersection of A and 2. Next, A3 is calculated as the average of SNR under A3, which is 1/9(-155.6002 -100.5846-149.5798 -155.6002 -100.5896 -149.5798 -155.6002 -100.6032 -149.5798) which give a value of -135.2575. The same approach is used to evaluate the average SNR for each item of factor under each level (Table 3).

This table is then referred to as the average signal-to-noise ratio for the parameters. Table 3 shows some interesting results about the optimal parametric settings and the delta values. The delta value for each parameter is computed as the difference between the highest and lowest values in the column represented by the factors. For factor A, the highest value is obtainable at level 1 as -129.445 while the lowest value is obtained at level 2, which is -137.0711. The difference between these two values is 7.5261. This difference in value is written as the second to the last row of Table 3. The other delta values are so computed, which range from the lowest value of 0.1107 (parameter D) to the highest value at parameter F (i.e. 59.0066). According to the principle of ranking, the highest delta value is given the first position, which is parameter F, while the lowest delta value is assigned the last position (i.e. parameter D is assigned the sixth position). Next, the ranks obtained for the parameters F, E, A, B, C, and D are 1st, 2nd, 3rd, 4th, 5th, and 6th

Table 4. Delta ratios (Taguchi method)

Ratios	A	B	C	D	E	F
Delta/HOPV	-0.0581	-0.0009	-0.0008	-0.0008	-0.05814	-0.6109
Delta/LOPV	-0.05491	-0.0009	-0.0008	-0.0008	-0.05491	-0.3792
Delta/AOPV	-0.0562	-0.0009	-0.0008	-0.0008	-0.0562	-0.4406
Delta ratio	553.0316					
Delta variability	58.8959					
Mean delta value	12.3993					
Median delta value	3.8206					

Key: A = Revenue in the packing industry, for a year (2015) -{Million dollars}; B = Packing Units sold (Billion); C = CAGR-2015; D = Packing Materials; E = Quantity consumed in kilotons; F = CO2e of Packing materials; HOPV= Highest optimal parametric value in the column representing the parameters; LOPV= Lowest optimal parametric value in the column for each parameter; AOPV= Average optimal parametric value along the parametric assessment column; Delta ratio= Highest delta value divided by the lowest delta value; Delta variability= Difference between the highest delta value and the lowest delta value; Mean delta value= Average of all delta values; Median delta values= Middle term for delta values

Table 5. Normalization of decision matrix

Level	Parameters					
	A	B	C	D	E	F
1	0	0	0	0	0	0
2	1	0.29	0.31	0.28	0.76	0.90
3	0.76	1	1	1	1	1
Standard deviation	0.522	0.514	0.512	0.532	0.545	0.551

positions, respectively. Then the optimal parametric setting is determined by finding out the highest average signal-to-noise ratio for each factor, which is obtained for factors A to F at A_1, B_1, C_1, D_1, E_1, and F_1, respectively. It is stated as follows: The optimal parametric setting is $A_1B_1C_1D_1E_1F_1$, which is interpreted as 52 million dollars of revenue attained in the packing industry, 127 billion packing units sold, 0.77 of compound annual growth rate, 1.5 materials used for packing, 5581 quantity consumed in kilo tons, 1 carbon dioxide equivalent of packing materials. Furthermore, having calculated the rest of the average SNRs for B1, B2, B3, C1, C2, C3, D1, D2, D3, E1, E2, E3, F1, F2, and F3, a complete response table is obtained, referred to as the direct parameter based response table since all the entries are obtained by assuming that the parameters that generate them are direct parameters. The interpretation of Table 3 is made according to the following elements: (1) the optimal parametric settings (2) Delta values and (3) the Ranks of the parameters. For more explanations, other ratios are derived from the results, which are (1) the Delta ratio, known as the highest delta value divided by the lowest delta value (Table 4) (2) Delta variability, which is the best minus the worst delta value (Table 4) (3) Mean delta value, which is the average of all the delta values (Table 4) (4) Median delta value, which is the middle term of all the delta values (Table 4) (5) Delta to highest optimal parametric value, which is the value of the delta divided by the value of any of the parameters with the highest parametric setting (Table 4) (6) delta to lowest optimal parametric value, which is the value of the delta divided by the value of the least parametric value at optimal setting (Table 4) (7) Delta to an average optimal value, which is the value of the delta to the mean of all parametric setting values.

Moreover, in Table 3, the optimal parametric setting, delta values, and rank of parameters have been evaluated for the vehicle emission problem. However, the innovative method proposed in this work integrates the Taguchi method and the VIKOR methods. In the first case, the Taguchi method is integrated with VIKOR as the Taguchi-VIKOR method. In this instance, the output of the Taguchi method which is meant to be the input to the VIKOR method is the average signal-to-noise ratio. However, an attempt was made to apply the VIKOR method. In this attempt, a weighting factor is necessary to be assigned to the VIKOR method before the final evaluation can be made. This is the pre-processing of the VIKOR method entails the weighting method which can be used as an average method. The average method is found by dividing a unit by the number of parameters involved in the process. In the present situation where six parameters are involved, the weight could be 1 divided by 6 which is 0.1667. This value is subjective and an objective value could be used by using the critic method to evaluate the weight of criteria. Therefore in the following discussion, the CRITIC method is used to evaluate the weight of parameters for the six parameters involved in this work. The starting point is to normalize Table 3 which contains the average signal-to-noise ratios. In the normalization, a range of 0 to 1 is set for the values at the lower and upper boundaries. Notice that Table 3 shows the best and worst values for the six parameters of the vehicle emission process. For instance, for parameter A, along column A, the best value is - 137.0711 while the worst value is -129.445. Based on Equation (3), to calculate the normalized value, the X_{ij} bar is used. In the particular case of interest where the intersection between level 1 and parameter A is to be obtained, the X_{ij} bar is the ratio of the numerator to the denominator of Equation (3). Table 5 shows the results of the normalization. Moreover, the adjusted normalized matrix is obtained by adding a dummy zero value to modify the matrix structure to one that could accommodate transformation to correlation coefficients, Table 6.

Table 6. Adjusted normalized matrix

Parameters	Parameters					
	A	B	C	D	E	F
A	0	0	0	0	0	0
B	1	0.29	0.31	0.28	0.76	0.90
C	0.76	1	1	1	1	1
D	0	0	0	0	0	0
E	0	0	0	0	0	0
F	0	0	0	0	0	0

Table 7. Correlation matrix

Parameters	Parameters					
	A	B	C	D	E	F
A	1.0000	0.7258	0.7395	0.7188	0.9457	0.9737
B	0.7258	1.0000	0.9996	0.9999	0.9099	0.8634
C	0.7395	0.9996	1.0000	0.9995	0.912	0.8735
D	0.7188	0.9999	0.9995	1.0000	0.9057	0.8583
E	0.9457	0.9099	0.912	0.9057	1.0000	0.9949
F	0.9737	0.8634	0.8735	0.8583	0.9949	1.0000

Table 8. The measure of conflict table

Parameters	Parameters						Measure of conflict
	A	B	C	D	E	F	$\sum_{i=1}^{m}(1-r_{jk})$
A	0.0000	0.2742	0.2605	0.2812	0.0543	0.0263	0.8965
B	0.2742	0.0000	0.0004	0.0001	0.0901	0.1366	0.5014
C	0.2605	0.0004	0.0000	0.0005	0.088	0.1265	0.4759
D	0.2812	0.0001	0.0005	0.0000	0.0943	0.1417	0.5178
E	0.0543	0.0901	0.088	0.0943	0.0000	0.0051	0.3318
F	0.0263	0.1366	0.1265	0.1417	0.0051	0.0000	0.4362

The numerator is – 129.445 -(-129.445). However, the denominator is -137.6711 - (1 - 129.445), which gives a value of 0 when the numerator is placed on the denominator. Based on the computations, Table 5 is now obtained which shows the value of the X_{ij} bar for all levels and all factors. For Table 5 an additional row is created which is the standard deviation for each parameter for all three levels. For parameter A where the values considered are 0, 1, and 0.76 for levels 1, 2, and 3, the standard deviation is obtained as 0.522. Similar computations are made for all parameters B to F to obtain their standard deviations.

Next, an adjusted normalized matrix is computed to make the matrix a square form in this case parameters A to F, which as six entries did not match levels 9 to 3 that has three entries (Table 6). As part of the adjustment, three dummy levels are created with values of zero entered for them. It is then allowed to analyze a square matrix for correlation analysis. Accordingly, the horizontal axis of the matrix is lettered A to F while the vertical axis of the matrix is lettered A to F, this means that the rows having the first, second, and third dummies will be D, E and F. Table 7 shows the correction matrix. This is obtained by placing the values of two sets for the same parameter for correlation analysis. For instance, at the intersection of parameter A with parameter B, the values along the *X*-axis will be taken as 0, 0, 0, 0, 0, and 0 along the *Y*-axis the values of 0, 0.29, 1, 0, 0, and 0 will be taken when correlation test in a run for this two set of value 0.7258 is obtained and this is placed in the correlation matrix. All other analyses are considered similarly. The range of correlation is from the worst value of 0.7188 to the best value of 1 where all the values reveal acceptable thresholds between pairs of parameters.

The next process is to evaluate the measure of conflict. Here the diagonal element is zero, which is a measure of the conflict of a parameter against itself (Table 8). Considering parameter A as the base point along the horizontal scale, the measure of conflict of A against B is 0.2742, and against C, D, E, and F are, 0.2605, 0.2812, 0.0532, and 0.0263, respectively. Now, along the horizontal, the values under each parameter are added to have 0.8965 for parameter A, 0.5014, 0.4759, 0.5778, 0.3318, and 0.4362 for parameters B to F, respectively (Table 8).

Now, Table 9 shows the parameter at the center were the standard deviations go to the left and the measure of conflict is placed on the right-hand side of the parameters. Next, by considering the standard deviation and the measure of conflict in a product sense the quality of information in each criterion (parameters) is obtained as C_j. By obtaining the ratio of C_j to the sum, the weight of each parameter is obtained through the CRITIC method as W_1, W_2, W_3, W_4, W_5, and W_6 as 0.2826, 0.1559, 0.1471, 0.1013, 0.1046 and 0.1484 for parameters A to F, respectively (Table 10). These weights of parameters,

Table 9. Standard deviation and measure of conflict

Parameters	Standard deviation	The measure of conlict: $\sum_{i=1}^{m}(1-r_{jk})$
A	0.5220	0.8965
B	0.5149	0.5014
C	0.5119	0.4759
D	0.5159	0.5178
E	0.5220	0.3318
F	0.5508	0.4362

Table 10. Weights of parameters

Parameters	c_j	W_j
A	0.4580	0.2826
B	0.2582	0.1559
C	0.2436	0.1471
D	0.2671	0.1613
E	0.1732	0.1046
F	0.1732	0.1484

Table 11. Unity measure

Weightage	0.2826	0.1559	0.1471	0.1613	0.1046	0.1484	S_i
Level	A	B	C	D	E	F	
1	0.2826	0.1559	0.1471	0.1613	0.1046	0.1484	0.9990
2	0.0000	0.1099	0.1022	0.1154	0.0249	0.0151	0.3675
3	0.0672	0.0000	0.0000	0.0000	0.0000	0.0000	0.0672

obtained through the CRITIC method are then introduced into the VIKOR method. The results here are those first optimized by the Taguchi method and then moved upon by the VIKOR method. The outputs of this method are the ranks of the criteria, which is the combination effect of the unity measure and the individual regrets of the criteria.

The next step is to obtain the unity measure, which is shown in Table 11, by employing Equation (4). To illustrate how this is done, consider the intersection of A and level 1, where the weight for A, which is obtained using the CRITIC method gives 0.2826. This value is multiplied by the numerator, which is the difference between X_{best} and X_{ij}, and the denominator which is the difference between X_{best} and X_{worst}. By doing this calculation, a value of 0.2826 is obtained.

Also, by following this method, values at intersection, namely, B1, C1, D1, E1 and F1 give 0.1559, 0.1471, 0.1613, 0.1046 and 0.1484, respectively. The addition of the values at S_i, which is the unity measure, gives 0.9990. To obtain Ri, the maximum is taken as 0.2826. The next step is shown in Table 12 where S^-, R^- and S*, R* are calculated. Finally, Table 13 shows the ranks of the criteria, which is the final result for the Taguchi-VIKOR method through the CRITIC route.

Table 12. S_i and R_i's scores

Level (criteria)	S_i	R_i
1	0.999	0.2826
2	0.3675	0.1154
3	0.0672	0.0672
S*	0.999	0.2826
S-	0.0672	0.0672

Table 13. Quality and rank of criteria

Level (criteria)	S_i	R_i
1	1	3
2	0.2730	2
3	0	1

4.2. Taguchi-Pareto-VIKOR method

The Taguchi parent method ends with the analysis of the average signal-to-noise ratios, which produces signal-to-noise ratios (averages) based on the 80-20 rule where values above 80% are cut off from the cumulative signal-to-noise stage where ranks and delta values are also computed. To apply the Taguchi-Pareto-VIKOR method, reference is made to the cumulative signal-to-noise ratios computed in Table 1 which contains a cut-off close to 80% as 81.86%, which suggests an exclusion of run orders 23, 24, 25, and 27 from the calculation of the average signal to noise ratios. It implies that while still maintaining the six parameters, some orthogonal matrix entries will be missing once it involves any of those assigned to serial numbers 23 to 27. Moreover, this method started with the evaluation of the parametric settings, delta, and ranks for the Taguchi method when the experimental trials accounting for over 80% of the signal-to-noise ratio values have been removed. The removed experimental trials are from 22 to 27, which consist of roughly 18.14%. Moreover, based on the execution of the Taguchi-Pareto principle on the data of vehicle emission,

Table 14. Summary of the irrespective table and CRITIC results for part A of Taguchi ABC VIKOR method

Description	A	B	C	D	E	F
Best average S/N value	-155.6002	-136.3871	-136.5317	-136.4304	-152.5900	-155.6002
Worst average S/N value	-129.445	-133.2349	-133.1859	-133.1761	-121.972	-94.5942
Delta	26.1552	3.1522	3.3458	3.2543	30.618	61.006
Rank	3	6	4	5	2	1
Standard deviation	0.5143	0.5667	0.5732	0.5623	0.5146	0.5511
Measure of conflict	2.8808	6.1667	3.4236	3.6093	3.017	2.3206
Quality Index	0.1482	03.4904	1.9624	2.0295	1.5525	1.279
Weight in CRITIC	0.0142	0.338	0.1877	0.1941	0.1485	0.1223

Table 15. Criteria and ranks

Criteria	1	2	3
Q_i	0.5	0.5	0.7303
Rank based on Q_i	1	1	2

the ranks of parameters are F, E, A, C, D, and B, as 1st, 2nd, 3rd, 4th, 5th, and 6th position, respectively. Furthermore, to attain the weight classification by the CRITIC method, a normalized matrix consisting of parameters A to F along the horizontal path was made while along the vertical axis, the levels were used. However, it is desired to have a square matrix for the results. Therefore, a transformation of levels of factors is made, necessitating the addition of a dummy now consisting of zero elements along the rows representing D, E, and F. With this, it becomes easy to obtain the correlations between rows and columns. This effort led to the computation of the measure of conflict among the parameters. Moreover, by placing the standard deviation of each parameter against the calculated measure of conflict, the quality in relation to each parameter is calculated which measures 9.4094.

However, each parametric value for the vehicle emission process should be scale of 1 such that the sum of the weights using the CRITIC method yields 1. This was done and the results of weights for parameters A to F are 0.1023, 0.3297, 0.1625, 0.1419, 0.1093, and 0.1541, respectively. These are the weights assigned to each parameter when applied to the average signal-to-noise ratios computed through the application of the 80 – 20% rule to the signal-to-noise ratios obtained from the vehicle emission data. This commences the application of the VIKOR method to solve the problem where the Taguchi-Pareto-VIKOR method is known to have been used in vehicle emission data. The utility measure Si is obtained, which are 0.6704, 0.4978, and 0.4565 for levels 1 to 3. When the regret measure is used, levels 1 to 3 have 0.1625, 0.3297, and 0.1089, respectively. By calculating Qi from the combination utility and regret measures, the final values of Qi are Q1, Q2, and Q3 of 3rd, 2nd, and 1st for levels 1, 2, and 3, respectively. These are the results of the Taguchi-Pareto-VIKOR method. The obtained results of the Taguchi-Pareto method, which considers only 80% of the experimental trials are used by the VIKOR method to produce Qi, which is the combination of unity measure and individual regret.

4.3. Taguchi-ABC-VIKOR method

Part A of the Taguchi-ABC-VIKOR method

The foundation of the ABC-based computation for the present process is the analysis of the cumulative signal-to-noise ratios into three separate parts. These are the 70%, 20 and 10% for the parts A, B and C, respectively. In essence, after computing the cumulative signal-to-noise ratios, a value between 0% and 70% is identified and the experimental trials concerning these are the ones that will firm the computational basis of the average signal-to-noise ratios for the evaluation of the optimal parametric settings, delta values and the ranks of the parameters. In the computation of the cumulative signal-to-noise ratios for the vehicle emission process, only approximately 70% was obtained, which is 70.63362% at serial number 19 of the experimental trials. In Table 14 the summary of the analysis concerning parameters A to F.

From the perspective of average signal-to-noise ratios (response table) for the part A of the Taguchi-ABC, weights of parameters (using the CRITIC method), Qi values and ranks are shown in Table 15. The ranks obtained from the average signal-to-noise ratios are F, E, Q, C, D, and B as 1st, 2nd, 3rd, 4th, 5th, and 6th parameters, respectively. The weights obtained from the CRITIC methods, which serve as inputs in the computation of the VIKOR methodical aspect of the proposed method are 0.0142, 0,3338, 0.1877, 0.1941, 0.1485 and 0.1223, for the respective factors of A to F. after computing the VIKOR outputs, for criteria 1, 2 and 3, the Q1, Q2 and Q3 obtained are 0.5, 0.5 and 0.7303 and the ranks and 1st, 2nd and 2nd, respectively part B of the Taguchi-ABC-VIKOR method.

By starting from the cumulative signal-to-noise ratios obtained for the Taguchi method, it was noticed that for part B, which is 20% above part A, a target of 90% cut–off is essential to use. It implies that the cut-off will be serial number 24 with a cumulative value of 88.726% is considered. However, part B elements are those above 70% but less or equal to 90%. Therefore, the captured elements are serial numbers 20, 21, 22, 23, and 24. These have cumulative values between 73.4179% and 88.7762% and one is then used for further computations. In Table 16, the analysis concerning parameters A to F is

Table 16. Summary of response table and CRITIC results for part B of Taguchi-ABC-VIKOR method

Description	A	B	C	D	E	F
Best average S/N value	-131.1868	-135.2565	135.2565	-135.345	-135.6002	-155.6002
Worst average S/N values	0	0	0	0	-100.5871	-100.5871
Delta	-131.1868	135.2565	135.2565	135.2565	55.0131	55.0131
Rank	2	1	1	1	1	3
Standard deviation	0.5774	0.5569	0.5569	0.5569	0.5502	0.5502
Measure of conflict	3.1505	4.0033	2.5936	3.3359	4.1423	2.5128
Quality Index	1.8191	2.2294	1.4459	1.8575	2.2791	1.410
Weight in CRITIC	0.1648	0.2019	0.1310	0.1682	0.2064	0.1277

Table 17. Criteria and ranks

Criteria	1	2	3
Q_i	0.4098	0.9898	0.4397
Rank based on Q_i	1	3	2

Table 18. Fuzzy numbers and their respective numerical values

Linguistic term	Numerical value	Fuzzy number
Equal	1	1,1,1,1
Moderate	3	2,3,4,5
Strong	5	4,5,6,7
Very strong	7	6,7,8,9
Extremely strong	9	9,9,9,9
Intermediate values	2	1,2,3,4
	4	3,4,5,6
	6	5,6,7,8
	8	6,7,8,9

summarized in terms of the response table results and CRITIC methods computational essentials.

Table 17 shows the ranks obtained coupled with the Qi values for the criteria. The ranks obtained from the average signal to noise ratios are B, C. D, E, A and F as 1st, 1st, 1st, 1st, 2nd and 3rd, respectively. The weights obtained from the CRITIC method which were introduced into the computational framework of the VIKOR method are 0.1648, 0.2019, 0.1310, 0.1682, 0.2064, and 0.1277, respectively. After computing the VIKOR method, criteria 1, 2, and 3 have the respective Q1, Q2, and Q3 of 0.4098, 0.9898, and 0.4397 with the respective ranks of 1st, 3rd and 2nd. Moreover, after computing the signal-to-noise ratios from the factor-level table, the run orders are separated into three compartments, which are the A, B, and C categories. According to the compartments, the optimal parametric settings and average signal-to-noise levels are computed and the latter are connected to the weight of the criteria, which are then used to calculate Qi used to assess the criteria based on the combination of unity measure and individual regret.

4.4. Fuzzy VIKOR

In this section, the fuzzy VIKOR method is applied by obtaining data from the literature. Specifically, the Table of Benrajesh and Rajan (2019) was used as the foundation to discuss the fuzzy methodology and its application to logistics and packing industries. The fuzzy scale of relative importance is the first step in the evaluation of fuzzy VIKOR. Here the fuzzy numbers and their respective numerical values are defined (Table 18).

For the numerical value of 1 to be translated into a fuzzy number using a triangular method, a fuzzy number of 1,1,1, is obtained. However, in the present study, the trapezoidal membership function area was formulated. Since there are four points in the trapezoid, the fuzzy number for numerical value 1 is 1,1,1,1. However, for numerical value 2 which has three items considering triangular function, the corresponding value of fuzzy number is 1,2,3,4. By following the same idea, all the fuzzy number corresponding to numerical values 1 to 9 is developed (Table 18). Next, is the pairwise comparison matrix (Table 19).

Here, the ranks of the parameters are extracted from Table 3 which shows the direct parameter response table using the Taguchi method. Then, the parameters along the first column (i.e parameters A, B, C, D, E, and F) are compared with those on the second row (i.e parameters A, B, C, D, E, and F), thus using their rank, the highest rank is F. Thus, if parameters that are equal such as A and A, B, and B, C and C, and so on, are compared, a value of 1 is assigned on the fuzzy scale on the fuzzy scale of relative importance, for others, they are either in whole number or fractions. The results are shown in Table 19. Next is the translation of Table 19 into a fuzzy pairwise comparison matrix, where the numerical values are read in terms of fuzzy members. For instance, the intersection of parameter A with parameter A, which was written as numerical value 1, will be translated into 1,1,1,1 (Table 20).

Other values in Table 20 are calculated likewise. Next is the fuzzy geometric mean, which uses the formula in Equation (6). The results are presented in Table 21.

Table 19: Pairwise Comparison Matrix

Parameter	Rank by delta values	Parameter					
		A	B	C	D	E	F
		3	4	5	6	2	1
A	3	1	2	4	5	1/2	1/4
B	4	1/2	1	2	4	1/4	1/5
C	5	1/4	1/2	1	2	1/2	1/6
D	6	1/5	1/4	1/2	1	1/6	1/7
E	2	2	4	5	6	1	1/2
F	1	4	5	6	7	2	1

Table 20: Fuzzy Pairwise Comparison Matrix

Parameter	A	B	C	D	E	F
A	1, 1, 1, 1	1, 2, 3, 4	3, 4, 5, 6	4, 5, 6, 7	1/4, 1/3, 1/2, 1	1/6, 1/5, 1/4, 1/3
B	1/4, 1/3, 1/2, 1	1, 1, 1, 1	1, 2, 3, 4	3, 4, 5, 6	1/6, 1/5, 1/4, 1/3	1/7, 1/6, 1/5, 1/4
C	1/6, 1/5, 1/4, 1/3	1/4, 1/3, 1/2, 1	1, 1, 1, 1	1, 2, 3, 4	1/7, 1/6, 1/5, 1/4	1/8, 1/7, 1/6, 1/5
D	1/7, 1/6, 1/5, 1/4	1/6, 1/5, 1/4, 1/3	1/4, 1/3, 1/2, 1	1, 1, 1, 1	1/8, 1/7, 1/6, 1/5	1/9, 1/8, 1/7, 1/6
E	1, 2, 3, 4	3, 4, 5, 6	4, 5, 6, 7	5, 6, 7, 8	1, 1, 1, 1	1/4, 1/3, 1/2, 1
F	3, 4, 5, 6	4, 5, 6, 7	5, 6, 7, 8	6, 7, 8, 9	1, 2, 3, 4	1, 1, 1, 1

Table 21. Fuzzy geometric mean (trapezoidal rule)

Parameter	Fuzzy geometric mean value r_i
Revenue in the packing industry for a year (2015) - {Million dollars} (A)	0.8909, 1.1776, 1.4969, 1.9560
Packing Units sold (Billion) (B)	0.5113, 0.6680, 0.8219, 1.1225
CAGR-2015 ©	0.3010, 0.3834, 0.4817, 0.6368
Packing Materials (D)	0.2087, 0.2415, 0.2900, 0.3749
Quantity Consumed in Kilotons €	1.5704, 2.0758, 2.6085, 3.3220
CO_2e of Packing Materials (F)	2.6672, 3.4479, 4.1407, 4.7912

Table 22. Weight and normalized weight for parameters

Parameter	Weight	Normalized weights
A	1.3804	0.1526
B	0.7809	0.0863
C	0.4507	0.0498
D	0.2788	0.0308
E	2.3942	0.2646
F	3.7618	0.4158

Table 22 shows the fuzzy weighted average the normalized weighted average and the normalized weight for each parameter. Consider parameter A, for instance, the fuzzy weight of this parameter was obtained by finding the average of the fuzzy geometric mean value. Thus, the average of 0.8999, 1.17776, 1.4969 and 1.9560 is 1.3804. The weights for other parameters such as B to F are also obtained in a similar manner. However, to obtain the normalized weight for each parameter, the fuzzy weights are added for all the parameters, and the weight for each parameter is taken as the ratio of the total. The results are discussed in Table 22.

Furthermore, these weights are placed along with each parameter such that Equation (4) is used to evaluate the unity measure at each level. The results are shown in Table 23. In Table 23, the values along each level are added across each parameter to obtain the unity measure, which gives 0.9999 for level 1. Other values are obtained as 0.2153 and 0.0363 respectively. Furthermore, Ri is calculated (i.e. Equation (5, which is the maximum of all the entries under each parameter for each level. This is shown in Table 24. Finally, the ranks are shown in Table 25. By comparing fuzzy VIKOR and Taguchi-VIKOR methods, the two results are the same.

5. CONCLUSIONS

This paper contributes to the logistics literature by offering three robust methods for the joint optimization of process parameters. The Taguchi method, which serves as the basis of the methods proposed in this work exhibits the distinct indices of delta in the forms of delta ratio, delta variability, mean delta value, median delta value, delta/HOPV, delta/LOPV, and delta/AOPV, which are defined by the present research for the first time in the literature. It provides a basis of enhanced assurance to select the adequate parameter of the emission in logistics and packing industries. The novel aspects of this work are as follows: (1) for the first in the optimization literature concerning the logistics and packaging industry using the Taguchi method, the following new ratios are introduced and verified: Delta ratio, delta variability, mean delta

Table 23. Computation of unity measure for parameters using fuzzy VIKOR method

Level	Parameter						
	A	B	C	D	E	F	Si
1	0.1526	0.0863	0.0498	0.0308	0.2646	0.4158	0.9999
2	0	0.0609	0.0346	0.0218	0.0556	0.0424	0.2153
3	0.0363	0	0	0	0	0	0.0363

Table 24. Computation of R_i

Criterion	S_i	R_i
1	0.9999	0.4158
2	0.2153	0.0556
3	0.0363	0.0363
S-,R-	0.9999	0.4158
S*,R*	0.0363	0.0363

S_i: Unity measure; R_i: Individual regret

Table 25. Ranks of parameters

Criterion	Q_i	Rank
1	1.0000	3
2	0.1183	2
3	0.0000	1

Table 26. Comparison of ranks of parameters

Criterion	Q_i	Fuzzy VIKOR method	Q_i	Taguchi-VIKOR method
1	1.0000	3	1.0000	3
2	0.1183	2	0.2730	2
3	0.0000	1	0.0000	1

value, median delta value, delta/HOPV, delta/LOPV, and delta/AOPV. The paper stands out from other previous applications of the Taguchi method for the same problem. The differences are the introduction of the delta variants, Pareto, ABC, and VIKOR methods. Future research opportunities should center on capturing uncertainties with the use of hesitant fuzzy methods and their combination with the linguistic fuzzy method while applied within the context of Taguchi-VIKOR, Taguchi-ABC-VIKOR, and Taguchi-Pareto-VIKOR. Robust optimization and selection schemes for exhaust emission from logistics and packing industries using Taguchi-fuzzy-VIKOR, Taguchi-Pareto-fuzzy-VIKOR, and Taguchi-ABC-fuzzy-VIKOR methods.

REFERENCES

Akman, G. (2015). Evaluating suppliers to include green supplier development programs via fuzzy c-means and VIKOR methods. *Computers & Industrial Engineering, 86*, 69-82.

Awasthi, A., & Kannan, G. (2016). Green supplier development program selection using NGT and VIKOR under fuzzy environment. *Computers and Industrial Engineering*, *91*, 100-108.

Bai, C., & Sarkis, J. (2010). Green supplier development: analytical evaluation using rough set theory. *Journal of Cleaner Production, 18*(12), 1200-1210.

Benrajesh, P., & Rajan, A.J. (2019). Optimizing the exhaust emission from logistics and packing industries, by means of green logistics. *Journal of Physics Conference Series*, *1355*(1), Article 012019.

Bodendorf, F., Dimitrov, G., & Franke, J. (2022). Analyzing and evaluating supplier carbon footprints in supply networks. *Journal of Cleaner Production, 372*, Article 133601.

Buyukozhan,G., & Cifci, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP, and fuzzy TOPSIS to evaluate green suppliers. *Expert Systems with Applications, 39*(3), 3000-3011.

Chatterjee, K., Pamucar, D., & Zavadskas, E.K. (2018). Evaluating the performance of suppliers based on using the R'AMATEL-MAIRCA method for green supply chain implementation in electronics industry. *Journal of Cleaner Production, 184,* 101-129.

Datta, S., Samantra, C., Mahapatra, S.S., Banerjee, S., & Bandyopadhyay, A. (2012). Green supplier evaluation and selection using VIKOR method embedded in fuzzy expert system with interval-valued fuzzy numbers. *International Journal of Procurement Management*, *5*(5), 647-678.

Demir, L., Akpinar, M.E., Araz, C., & Ilgin, M.A. (2018). A green supplier evaluation system based on a new multi-criteria sorting method: VIKORSORT. *Expert system with Applications, 114*, 479-487.

Dobos, I., & Vorosmarty, G. (2014). Green supplier selection and evaluation using DEA-type composite indicators. *International Journal of Production Economics*, *157*, 273-278.

Dou, Y., Zhu, Q., & Sarkis, J. (2014). Evaluating green supplier development programs with a grey-analytical network process-based methodology. *European Journal of Operational Research, 233*(2), 420-431.

dos Santos, B.M., Godoy, L.P., & Campos, L.M.S. (2019). Performance evaluation of green suppliers using entropy-TOPSIS-F. *Journal of Cleaner Production, 207*, 498-509.

Feng, J., & Gong, Z. (2020). Integrated linguistic entropy weight method and multi-objective programming model for supplier selection and order allocation in a circular economy: A case study. *Journal of Cleaner Production, 277*, Article 122597.

Fu, X., Zhu, Q., & Sarkis, J. (2012). Evaluating green supplier development programs at a telecommunications systems provider. *International Journal of Production Economics, 140*(1), 357-367.

Gao, H., Ju, Y., Gonzalez, E.D.R.S., & Zhang, W. (2020). Green supplier selection in electronics manufacturing: An approach based on consensus decision making. *Journal of Cleaner Production*, *245*, Article 118781.

Gao, H., Ju, Y., Gonzalez, E.D.R.S., Zeng, X., Dong, P., & Wang, A. (2021). Identifying critical causal criteria of green supplier evaluation using heterogeneous judgments: An integrated approach based on cloud model and DEMATEL. *Applied Soft Computing, 113,* Article 107882.

Garg, R.K. (2021). Structural equation modeling of E-supplier selection criteria in mechanical manufacturing industries. *Journal of Cleaner Production*, *311*, Article 127597.

Ghadimi, P., Sar, K., & Azadnia, A.H. (2024). An integrated decision-making process for sustainable supplier selection and order allocation in the automotive industry. *Procedia CIRP*, *122*, 1036-1041.

Ghorabaee, M.K., Zavadskas, E.K., Amiri, M., & Esmaeili, A. (2016). Multi-criteria evaluation of green suppliers using an extended WASPAS method with interval type-2 fuzzy sets. *Journal of Cleaner Production, 137*, 213-229.

Goodarzi, F., Abdollahzade, V., & Zeinalnezhad, M. (2022). An integral multi-criteria decision making and multi-objective optimization framework for green supplier evaluation and optimal order allocation under uncertainty. *Decision Analytics Journal, 4*(2), Article 100087.

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi-criteria decision-making approaches for green supplier evaluation and selection: a literature review. *Journal of Cleaner Production, 98,* 66-83.

Güneri, B., & Deveci, M. (2023). Evaluation of supplier selection in the defense industry using q-rung orthopair fuzzy set based EDAS approach. *Expert Systems with Applications*, *222*, Article 119846.

Hajiaghaei-Keshteli, M., Cenk, Z., Erdebilli, B., Özdemir, Y.S., & Gholian-Jouybari, F. (2023). Pythagorean fuzzy TOPSIS method for green supplier selection in the food industry. *Expert Systems with Applications*, *224*, Article 120036.

Haryono, Masudin, I., Suhandini, Y., & Kannan, D. (2024). Exploring scientific publications for the development of relevant and effective supplier selection methods and criteria in the food Industry: A comprehensive analysis. *Cleaner Logistics and Supply Chain*, *12*, Article 100161.

Jefroudi, M.T., & Darestani S.A. (2024). A decision support system for sustainable supplier selection problem: Evidence from a radiator manufacturing industry. *Journal of Engineering Research*, *12*(4), 867-877.

Kara, K., Acar, A.Z., Polat, M., Önden, İ., & Yalçın, G.C. (2024). Developing a hybrid methodology for green-based supplier selection: Application in the automotive industry. *Expert Systems with Applications*, *249*, Article 123668.

Kumar, S., & Barman, A.G. (2021). Fuzzy TOPSIS and fuzzy VIKOR in selecting green suppliers for sponge iron and steel manufacturing. *Soft Computing*, *25*(8), 6505-6525.

Liou, J.J.H., Chuang, Y., Zavadskas, E.K., & Tzeng, G. (2019). Data-driven hybrid multiple attribute decision-making model for green supplier evaluation and performance improvement. *Journal of Cleaner Production*, *241*, Article 118321.

Liou, J.J.H., Chang, M., Lo, H., & Hsu, M. (2021). Application of an MCDM model with data mining techniques for green supplier evaluation and selection. *Applied Soft Computing, 109*, Article 107534.

Lo, H., Liou, J.J.H., Wang, H., & Tsai, Y. (2018). An integrated model for solving problems in green supplier selection and order allocation. *Journal of Cleaner Production*, *190*, 339-352.

Lo, H.W. (2023). A data-driven decision support system for sustainable supplier evaluation in the Industry 5.0 era: A case study for medical equipment manufacturing. *Advanced Engineering Informatics*, *56*, Article 101998.

Masoomi, B., Sahebi, I.G., Fathi, M., Yildirim, F., & Ghorbani, S. (2022). Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach). *Energy Strategy Reviews, 40*, Article 100815.

Mousakhani, S., Nazari-Shirkouhi, S., & Bozorgi-Amiri, A. (2017). A novel interval type-2 fuzzy evaluation model based group decision analysis for green supplier selection problems: A case study of battery industry. *Journal of Cleaner Production, 168*, 205-218.

Nafei, A., Azizi, S.P., Edalatpanah, S.A., & Huang, C.Y. (2024). Smart TOPSIS: A neural network-driven topsis with neutrosophic triplets for green supplier selection in sustainable manufacturing. *Expert Systems with Applications*, *255*, Article 124744.

Norheim-Hansen, A. (2023). Green supplier development: What's in it for you, the buyer? *Business Horizons, 66*(1), 101-107.

Rahman, M.M., Bari, A.B.M.M., Ali, S.M., & Taghipour, A. (2022). Sustainable supplier selection in the textile dyeing industry: An integrated multi-criteria decision analytics approach. *Resources, Conservation & Recycling Advances*, 15, Article 200117.

Pérez-Velázquez, A., Oro-Carralero, L.L., & Moya-Rodrí, J.L. (2020). Supplier selection for photovoltaic module installation utilizing fuzzy inference and the VIKOR method: A green approach. *Sustainability* (Switzerland), *12*(6), Article 2242.

Sarkar, S., Modak, N.M., Giri, B.C., Sarkar, A.K., & Cardenas-Barron, L.E. (2022). Coordinating a supplier–retailer JELS model considering product quality assessment and green retailing. *Journal of Cleaner Production, 356,* Article 131658.

Sharafi, H., Soltanifar, M., & Lotfi, F.H. (2022). Selecting a green supplier utilizing the new fuzzy voting model and the fuzzy combinative distance-based assessment method. *EURO Journal on Decision Processes, 10,* Article 100010.

Shen, L., Olfat, L., Govindan, K., Khodaverdi, R., & Diabat, A. (2013). A fuzzy multi-criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences. *Resources, Conversation and Recycling*, *74*, 170-179.

Singh, R.R., Zindani, D., & Maity, S.R. (2024). A novel fuzzy-prospect theory approach for hydrogen fuel cell component supplier selection for the automotive industry. *Expert Systems with Applications*, *246*, Article 123142.

Sonar, H., Gunasekaran, A., Agrawal, S., & Roy, M. (2022). Role of lean, agile, resilient, green, and sustainable paradigm in supplier selection. *Cleaner Logistics and Supply Chain, 4*, Article 100059.

Wu, Q., Zhou, L., Chen, Y., & Chen, H. (2019). An integrated approach to green supplier selection based on the interval type-2 fuzzy best-worst and extended VIKOR methods. *Information Sciences*, *502*, 394 – 417.

Wu, X., & Liao, H. (2023). Geometric linguistic scale and its application in multi-attribute decision-making for green agricultural product supplier selection. *Fuzzy Sets and Systems, 458,* 182-200.

Yang, Y., & Jiang, Y. (2023). Does suppliers' slack influence the relationship between buyers' environmental, orientation and green innovation? *Journal of Cleaner Production, 157*, Article 113569.

Zhang, F., Li, Y., Li, F., Yuan, J., & Li, Y. (2022). Decision-making behaviour of power suppliers in the green certificate market: A system dynamics analysis. *Energy Policy, 171*, Article 113296.

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