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MEASURING SUSTAINABILITY PERFORMANCE INDICATORS USING FUCOM-MARCOS METHODS

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Abstract: *Due to rising environmental concerns, green innovation has become a familiar and appealing topic worldwide in recent years. In addition, population growth, globalization, urbanization, and industrialization have given rise to many problems, such as damage to the environment, the economy, and the living conditions of society. This paper aims to evaluate and prioritize aspects of green innovation, taking into account sustainability performance indicators. FUCOM-MARCOS hybrid methods were used. The experimental results of the proposed method showed that management technological innovation (C1) is the most influential part for adopting green practices in the textile industry in Nigeria. The study also showed that greening the supplier (C6) and product technology innovation (C5) are the second and third most important aspects of green innovation. Furthermore, it analyzed the sustainability performance indicators using the MARCOS method. The findings reveal that social performance (SPI-3) was the most sustainable and vital indicator in terms of green innovation practices in the textile sector in Nigeria. Sensitivity analysis was also conducted using five other methods, and the results obtained showed stability in the order of the indicators.*

Key words: *MCDM, MARCOS, FUCOM, Green innovation, performance indicators*

1. Introduction

Environmental degradation is caused by changing interplay of technology, institutional, and socio-economic ventures (Shujah-ur-Rahman et al., 2019). Environmental degradation has been stimulated by several elements, including

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transportation, rising energy, a sudden increase in agriculture, urbanization, population, and economic expansion. This has raised several environmental concerns in environmental conservation. Many countries are changing their business consumption and production models and emerging alleviation measures while generating an economic chamber that incorporates all environmental conservation measures.

Green innovation entails all kinds of innovations that industries and businesses participate in the formation of processes, services, or products that minimize declination impact and environmental harm and improve the use of typical resources (Singh et al., 2020). Green innovation magnifies an important capacity by directing the proper use of natural resources to better environmental conservation. Moreover, the formation and integration of changes in production and product processes provide sustainable developments (Glavič et al., 2021).

With the increasing economic activities and the increasing climatic change, manufacturing in the industries is indicating a big interest in tenable manufacturing. This has followed the implementation of several collective social responsibility initiatives. However, implementations of the initiatives in certain areas have been drawn back by growing consumption in other regions. Efficacity that has been attained in other areas has been outrun by scale effects. Governments give clear program indicators regarding their long-term and short-term climate change goals and the expense of climate program dimensions that can be maintained low. Improving effectiveness in resource and energy use and engaging in an extensive variety of innovations to better environmental performance will aid in forming new jobs and industries in the future. The ongoing economic crisis and agreements to confront climate change should be perceived as a chance to change to a greener economy (United Nations, 2020).

Manufacturing must be reorganized, and standing inventions technologies be extra innovatively enforced to conceive green growth. Brief relief packages set out in the present can excite investments in technologies and in fractures that aid innovation and empower changes in the ways we form and make use of products and services in the coming time. Industries have customary evaluated pollution anxiety at the core of discharge. They have minimized the number of materials and energy used in the production process as a cleaner production method (Chen & Wang, 2017).

In many manufacturing industries, they have focused on technological improvements and progression. However, several green innovations that are non-technological that as developing discrete environmental segmentation or forming multi-stakeholder or inter-sectoral study networks, have instigated technological advancements. Others have started to examine systemic innovations that are transforming consumer demand satisfaction.

Many manufacturing industries are contemplating the impacts of product lifecycle on the environment by blending environmental schemes and activities into their control systems (Zhang & Zhu, 2019). Some founders have planned on developing a closed-loop production system that does away with end product disposal by retrieving wastes and changing them into something different for production. Green innovation participates in making this a reality in industry practices. Once more incorporated practices such as closed-loop production are implemented, it can lead to great environmental upgrades by integrating of variety of innovation strategies with mechanisms and non-technological and technological changes.

With the high prices and shortage of materials, steel and iron industries have made consequential advancements in improving environmental conduct through several energy-saving alterations and redesigns of different production processes (Wong et al., 2020). Refreshed means of working inside the industry have resulted in a variety of these technological developments in products and processes potential. A good example is the collective working between steelmakers and vehicle designers which resulted in improved high-strength steel to produce lighter and more eco-friendly automobiles.

The electronic industry has concentrated on its energy consumption products. This is from the heightening consumer demands for electronic products, which is making them look for bigger productive means to get rid of their products into the environment. This makes many industries major in technological improvement inform of process redesign or product modification concerning environmental friendliness.

The transport and automotive industry has also implemented various strategies to mitigate carbon (IV) oxide discharge and other environmental influence remarkably those related to fossil-fuel combustion. In the advancing economies, there is increasing demand for mobility leading to industries majoring in improving the energy effectiveness of automobiles and other means of transit. Green innovation in automobile manufacturing has been achieved greatly by technological improvements. This is in areas such as maximization of the painting process, applying energy-saving tires, advanced power control systems, and improving fuel-injection technologies.

Government statutes and levels have participated in mitigating environmental damages to a vast extent although it is not the most valuable method to minimize emissions (Owen et al., 2018). It also does not give sufficient encouragement to innovate exceeding end-stage solutions. Conceiving the possibility of green innovations will demand actions to provide that complete rotation of innovations sufficient with strategies spanning from the endowment in study to advocate in profitable breakthrough technologies. Green innovation can guide notable economic chances. However, industries and business investors need plain and reliable pricing to enhance a greener future investment. Green innovations can help the environment and manufacturers. Additionally, green innovation represents proactive and cost-effective techniques that help companies to establish a sustainable competitive edge (Lin et al., 2015). Solutions and advancements to preventing industrial pollution will alleviate industrial pollution and damage to the environment.

However, the process of implementing green innovation in industries and businesses has some drawbacks (Peng et al., 2021). The barriers and drawbacks and barriers range from problems with financial challenges and poor team collaboration. Oftentimes, industries face inadequate internal mechanisms to discharge viable initiatives. The problems are based on a low capital allotment for the policies of green innovation. Managers disregard the necessity of minimizing exposure to energy price weightlessness and the environmental influence of their inward processes. This is a result of taking expenses connected with the same decisions extreme. Poor participation and difference in priorities and opinions of teams make engagement and implementation of green innovations hard. The project management team comes into action too late to make notable influence or change.

Today, businesses value sustainability policies as a means to achieve sustainable development (Asadi et al., 2020). In this context, Elkinton (1998) developed a model that includes economic, environmental, and social sustainability (i.e., triple bottom line) performance indicators to ensure environmental sustainability. Accordingly, economic, environmental, and social dimensions must be prioritized and balanced for an industry's sustainable development. Moreover, economic, environmental, and social concerns have heightened the significance of green innovation practices (Wang & Yang, 2021). The academic literature has also flourished in this area. However, the literature on green innovation frequently focuses on Western and developed countries (Cainelli et al., 2012; del Río et al., 2016). Therefore, this issue should be highlighted, as the literature on green innovation and sustainable performance practices for developing countries is surprisingly insufficient (Ullah et al., 2022). As such, the current research uses sustainability performance indicators (SPIs) suggested by Wang & Yang (2021) to evaluate the green innovation practices in Nigeria. Six aspects (criteria) of green innovation are used. The Balanced Score Card (BSC) structure developed by Kaplan and Norton (1992) is frequently used for sustainable performance evaluation (Aly & Mansour, 2017; Houck et al., 2012). However, this approach is inadequate as it cannot consolidate multiple performance factors. Since sustainable performance evaluation incorporates multiple criteria, this issue can be regarded as an MCDM (Multi-criteria decision making) problem (Lu et al., 2018). As such, the aspects of green innovation are evaluated using the Full Consistency Method (FUCOM) method. The ranking of the three SPIs is obtained using the Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) method using the weights of the aspects of green innovation obtained from the FUCOM analysis.

In the following respects, this work adds to the existing body of knowledge. Firstly, sustainable production is essential in the textile industry, which consumes large quantities of water, chemical loads, and energy from the cultivation of raw materials through the creation of completed items, as in other industries (Gbolarumi et al., 2021). Therefore, the textile industry is under significant pressure to address sustainability issues (Acar et al., 2015). Based on the importance of sustainability performance evaluation in the textile industry, this study advances the understanding of the literature on green innovation through empirical analysis. Second, to the authors' knowledge, this study is the first effort to highlight aspects of green innovation and SPIs in the textile industry in Nigeria. Therefore, this study is expected to provide important insights into green innovation to managers in the textile industry. This work adds to the literature by presenting for the first time the mathematically sound, integrated FUCOM-MARCOS technique to the area of sustainable performance assessment.

The remainder of the paper is structured as follows: Section 2 provides the research methodology that includes the FUCOM and MARCOS methods. In Section 3, a case study of a real-world application is presented through a two-stage sensitivity analysis. Finally, Section 4 concludes with a summary and suggestions for further study.

2. Research Methodology

MCDM is a technique utilized by researchers when making decisions involving the prioritization, ranking, or selection of preferences (Muhammad et al., 2021). Its goal is not to indicate the best conclusion but to help decision-makers in identifying nominated alternatives or a sole alternative that satisfies their needs and is in their favor. The MCDM system incorporates the behavior of preferences across many quantitative, qualitative, or conflicting criteria and consequences in a statement needing agreement. Various disciplines, such as information systems, economics, computer science, and behavioral decision theory, are leveraged for this purpose. Diverse MCDM techniques have been created, encouraged, and provided in a variety of necessity-driven contexts (Badi & Ballem, 2018). For example, Popović (2021) employed the CoCoSo method in solving the personnel selection problem. Similarly, Popović et al. (2021) adopted the SWARA methodology and examined the criteria affecting the recruitment and selection of staff. Özdağoğlu et al. (2021) proposed a comprehensive solution to the motorcycle selection problem consisting of MOPA, COPRAS, MOOSRA, WPM, SAW, and ROV methods.

MCDM techniques include, but are not limited to, analytical hierarchy process, simple additive weighting, data envelopment analysis, and analytical network process (Alosta et al., 2021). Despite numerous studies implementing the methods, MCDM continues to be a rapidly expanding issue in a number of departments. Nevertheless, each method has a similar capacity to make decisions in the face of distrust, and each has its own advantages.

In this research, a two-stage MCDM approach was used. During the first stage, the FUCOM method is utilized to calculate the weights of the criteria, and in the second stage, the MARCOS method is used to appraise the SPIs. The methodology can be divided into several steps as follows:

- Identify the significance and scope of the research

- Define the criteria that can be used in the study through previous studies

- Contacting experts to clearly define the idea of the model and the purpose of the study, as well as completing the form

- Calculating the weights of criteria using the FUCOM approach

- Obtaining the ranking of choices using the MARCOS approach

- Sensitivity analysis by using other methods of solution

Figure 1 also depicts the four-step flowchart of the research.

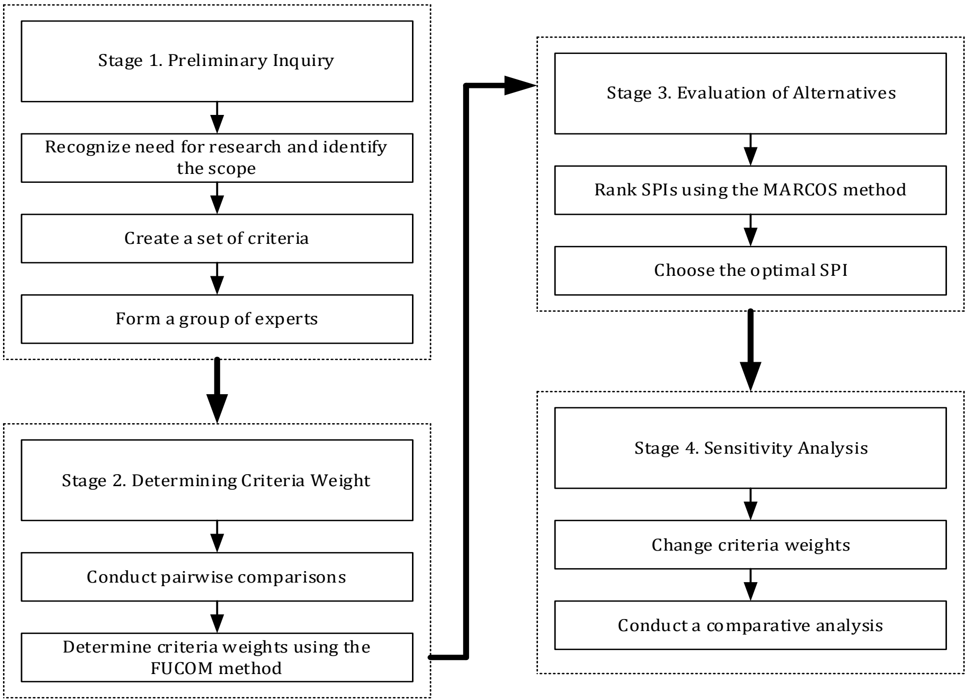

Figure 1. Flowchart of the proposed methodology

2.1 FUCOM method

Pamučar et al. (2018) have created FUCOM, one of the most recent MCDM models. This method uses the approach of pairwise comparison (Božanic et al., 2019). It requires fewer pairwise comparisons than alternatives such as the Best Worst Method (BWM) and the Analytical Hierarchy Process (AHP). In addition, it is capable of validating findings by describing the deviation from maximum consistency (DMC) of comparison and identifying transitivity in paired comparisons of criteria. It has been used in many applications in different areas of research (Fazlollahtabar et al., 2019).

In order to demonstrate the procedures of the method, we assume a number (n) of criteria that will be used to evaluate the decision (Pamucar et al., 2022). The decision-maker must determine the importance of each of these criteria by assigning a weight to them. In pairwise comparison models, the effect of each criterion (i) on the other criterion (j) is determined. The FUCOM method can be illustrated by the following steps (Badi & Kridish, 2020):

Algorithm: FUCOM

Input: Expert pairwise comparison of criteria

Output: Optimal values of the weight coefficients of criteria/sub-criteria

Step 1: Expert ranking of criteria/sub-criteria.

Step 2: Determining the vectors of the comparative significance of evaluation criteria.

Step 3: Establishing the constraints of a model for nonlinear optimization. Constraint 1: The percentage of weight coefficients for criteria represents the relative relevance of the given criteria. Constraint 2: The amount of weights must meet the mathematical requirement of transitivity.

Step 4: Creating a model for determining the final weights of assessment criteria.

Step 5: Computing the final weights of criteria and sub-criteria for appraisal.

3.2 MARCOS method

The MARCOS method involves calculating two reference alternatives, the ideal and the anti-ideal, and then determining the relative position of each alternative with respect to these two references (Stević et al., 2020). The position of this alternative within these two solutions is known as the usefulness function. After calculating these positions, one can find the best solution, which is the closest to the ideal and the furthest from the anti-ideal solution. Following are the steps necessary to describe this method (Badi & Pamucar, 2020):

Step 1: Establish an initial decision matrix.

Step 2: This stage involves the calculation of ideal and anti-ideal solutions for each alternative and the creation of an extended matrix utilizing these solutions. In this step, each of the alternatives is evaluated for each of the criteria, and the optimal and anti-optimal solutions of this alternative are calculated for these criteria. This step is performed according to the following equations:

$$AAI = \min_{j} x_{ij} \quad if \;\; j \in B \; and \;\; AAI = \max_{j} x_{ij} \quad if \;\; j \in C \tag{1}$$

$$AI = \max_{j} x_{ij} \quad if \;\; j \in B \; and \;\; AAI = \min_{j} x_{ij} \quad if \;\; j \in C \tag{2}$$

where B denotes the criterion that should be maximized and C denotes the criteria that should be minimized.

Step 3. The standardization of the initial extended matrix. Using the following equations, normalization is accomplished:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \; if \; j \in C \tag{3}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \; if \; j \in B \tag{4}$$

where the values x_{ij} and x_{ai} constitute the values of the initial decision matrix.

Step 4. The process of determining a weighted decision matrix. The weighting procedure is based on multiplying the normalized decision matrix values with the associated criteria weights.

Step 5. Computation of the usefulness degree for each alternatives *Ki.* Using the following formulae, we can calculate the usefulness degree::

$$K_i^- = \frac{S_i}{S_{aai}} \tag{5}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{6}$$

where S_i ($i=1,2,..,m$) is derived from the summation of the values of the weighted decision matrix.

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{7}$$

Step 6. The formulation of the usefulness function of the alternatives $f(K_i)$. Using the following equation, the function of usefulness is obtained as the final step.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \tag{8}$$

where $f(K_i^-)$ is the usefulness function based on the anti-ideal solution; on the contrary, $f(K_i^+)$ implies the usefulness function for the ideal solution. Both usefulness functions can be calculated with the help of the following equations, respectively.

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{9}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{10}$$

Step 7. Sorting the alternatives. At the end of the computation procedures, alternatives are ranked based on their usefulness functions. The most optimal solution must have the highest score for the usefulness function.

3. Case study

Extensive research highlights the growing concern about environmental issues in Nigeria. The textile industry is a major cause of pollution and the emission of harmful contaminants into the environment and is the second-largest source of industrial pollution in Lagos after the chemical and pharmaceutical industries. This pollution comes from the discharge of large quantities of toxins in high doses from the textile industry into the environment. The amount of toxic water with chemicals discharged amounts to more than 100 liters for every kilogram of textile product produced. These large quantities of water cause many textile manufacturers to discharge their effluents into nearby water bodies rather than into the sewage system. This has disastrous consequences for both aquatic life and the ability to supply fresh water. Therefore, given the importance of this industry in the country, it is essential that decision-makers give importance to ideas and policies that protect the environment (Durotoye et al., 2018). This research, therefore, aims to assess aspects of green innovation. The list of criteria in Table 1 will be used.

Table 1. The criteria list

Criteria No.	Evaluation criteria
C1	Technological innovation
C2	Competitive advantage
C3	Process innovation
C4	Managerial innovation
C5	Product innovation
C6	Greening the supplier

All of these criteria are profit-oriented. A total of four experts were involved in the evaluation process, during which the purpose of the research was explained to them, and the methodology to be used was clarified. Notable is the fact that four of the experts work in a field related to the industry sector, and two of them also hold academic positions. Therefore, experts have sufficient knowledge and experience regarding the subject and field of research. Purposive sampling was adopted in selecting experts, as experts need expertise in green innovation and the textile industry. As suggested by Gupta and Dhingra (2021), criteria weights were derived from a consensus-based group discussion to minimize the subjectivity of experts. The model will be described in the phases below:

First step: After discussion, the criteria were ranked in terms of importance in the following order:

C1> C6> C5> C3 >C2>C4

Second Step: The experts conducted a pairwise assessment of the criteria at this stage. All comparisons were made with criterion C1, which was defined as the most important criterion, and the scale [1,9] was used. Table 2 depicts the result of the comparison obtained.

Table 2. Prioritization of criteria

Criteria	C_1	C_6	C_5	C_3	C_2	C_4
$\varpi_{C_{j(k)}}$	1.0	2.0	3.0	4.0	4.0	5.0

Next, on the basis of the acquired criteria priorities, comparative criteria priorities must then be determined:

$$\varphi_{C_1/C_6} = 2.0/1.0 = 2.0, \varphi_{C_6/C_5} = 3.0/2.0 = 1.50, \varphi_{C_5/C_3} = 4.0/3.0 = 1.33$$

$$\varphi_{C_3/C_2} = 4.0/4.0 = 1.00, \varphi_{C_2/C_4} = 5.0/4.0 = 1.25$$

Third Step: In this procedure, the following two requirements are met by the final weight coefficients:

- That the values of these coefficients satisfy the condition in the second step, and these coefficient values can be written as follows:

$$\frac{w_1}{w_6} = 2.0, \frac{w_6}{w_5} = 1.50, \frac{w_5}{w_3} = 1.33, \frac{w_3}{w_2} = 1.0, \frac{w_2}{w_4} = 1.25$$

- That these values satisfy the mathematical transit condition, and it can be written as follows:

$$\frac{w_1}{w_5} = 3.0, \frac{w_6}{w_3} = 2.0, \frac{w_5}{w_2} = 1.33, \frac{w_3}{w_4} = 1.25$$

Consequently, the model for finding the weights of the criteria may be expressed as follows:

$$\min \chi$$

$$s.t \begin{cases} \left|\frac{\omega_1}{\omega_6} - 2{,}0\right| \le \chi, \left|\frac{\omega_6}{\omega_5} - 1{,}50\right| \le \chi, \left|\frac{\omega_5}{\omega_3} - 1{,}33\right| \le \chi \\ \left|\frac{\omega_3}{\omega_2} - 1{,}0\right| \le \chi, \left|\frac{\omega_2}{\omega_4} - 1{,}25\right| \le \chi, \left|\frac{\omega_1}{\omega_5} - 3{,}0\right| \le \chi \\ \left|\frac{\omega_6}{\omega_3} - 2{,}0\right| \le \chi, \left|\frac{\omega_5}{\omega_2} - 1{,}33\right| \le \chi, \left|\frac{\omega_3}{\omega_4} - 1{,}25\right| \le \chi \\ \sum_{j=1}^{5} \omega_j = 1, \omega_j \ge 0, \forall j \end{cases}$$

The final results of the weight coefficients and the CFD of the outcomes are acquired by solving this model. Figure 2 depicts the value of the criteria according to the first scores. Using the Microsoft Excel solver tool, the model is solved. Based on the observed data, it can be inferred that C1 is the most essential criterion, followed by C6. C4 is, however, the least important criterion.

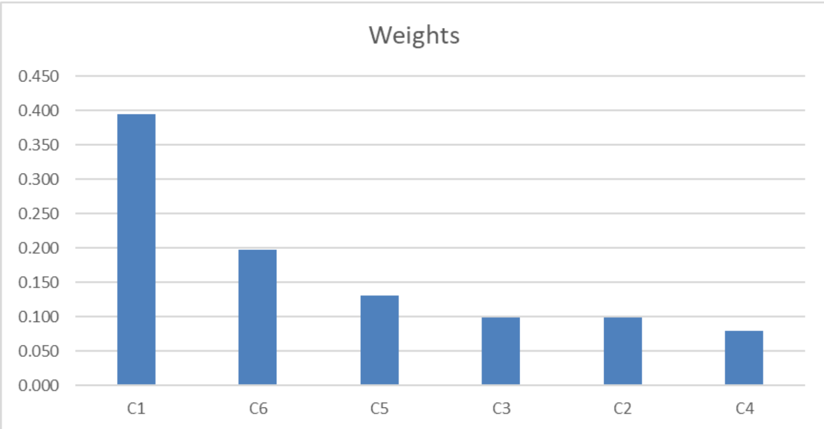

Figure 2. The value of decision criteria

After determining the criterion weights, the next step is to use the MARCOS method to rank the sustainability performance indicators. Based on the steps that have been explained in the second part of this research, the decision matrix obtained from the experts is prepared, as shown in Table (3). The sustainability performance indicators are SPI 1 (Economic performance), SPI 2 (Environmental performance), and SPI 3 (Social performance).

Table 3. The initial decision matrix

Weights of criteria	0.395	0.197	0.132	0.099	0.099	0.079
SPI #	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
SPI 1	57	55	45	52	62	50
SPI 2	52	58	47	55	57	51
SPI 3	60	57	53	51	62	51
MAX	**60**	**58**	**53**	**55**	**62**	**51**

A simple linear normalization is now used in order to obtain uninformed data. Since all the criteria used in the case of the study are profit criteria, the maximization function has been used. Applying equation (3), the normalized decision matrix is displayed in Table 4.

Table 4. The normalized decision matrix

SPI #	C1	C2	C3	C4	C5	C6
SPI 1	0.950	0.948	0.849	0.945	1.000	0.980
SPI 2	0.867	1.000	0.887	1.000	0.919	1.000
SPI 3	1.000	0.983	1.000	0.927	1.000	1.000

The next step is to use the coefficient weights previously found to obtain aggregated values. Then, the ideal solutions (i.e., the maximum values of a criterion) and the anti-ideal solutions (i.e., the minimum values of a criterion) are computed. The degree of usefulness is then calculated, and the findings are depicted in Table 5.

Table 5. The weighted decision matrix and the negative-ideal solution

SPI #	C1	C2	C3	C4	C5	C6	Sum
SPI 1	0.375	0.187	0.112	0.093	0.099	0.077	0.943
SPI 2	0.342	0.197	0.117	0.099	0.091	0.079	0.925
SPI 3	0.395	0.194	0.132	0.092	0.099	0.079	0.989
Ideal	0.395	0.187	0.132	0.092	0.099	0.079	0.983
Anti-ideal	0.342	0.197	0.112	0.099	0.091	0.077	0.918

Then, using equation 10, the usefulness function of each alternative is obtained by taking into account the usefulness function of the ideal and anti-ideal solutions. Thus, the ultimate ranking for the alternatives is identified in Table 6. It shows that the SPI 3 indicator is the most important sustainability performance indicator.

Table 6. The relative assessment matrix and alternative performance

SPI #	K_i^-	K_i^+	*F(ki)*	*Rank*
SPI-1	*1.028*	*0.960*	*0.661*	***2***
SPI-2	*1.007*	*0.941*	*0.648*	***3***
SPI-3	*1.078*	*1.007*	*0.694*	***1***

In order to measure the stability of the solution obtained, five other solution methods were used: CODAS (Keshavarz Ghorabaee et al., 2016), EDAS (Ghorabaee et al., 2015), MABAC (Pamučar & Ćirović, 2015), SAW (Goodridge, 2016), and WASPAS (Mardani et al., 2017). Figure 3 shows the results obtained. The results show the stability of the solution, except for indicators SPI-1 and SPI-2, which swap their order in the MABAC method.

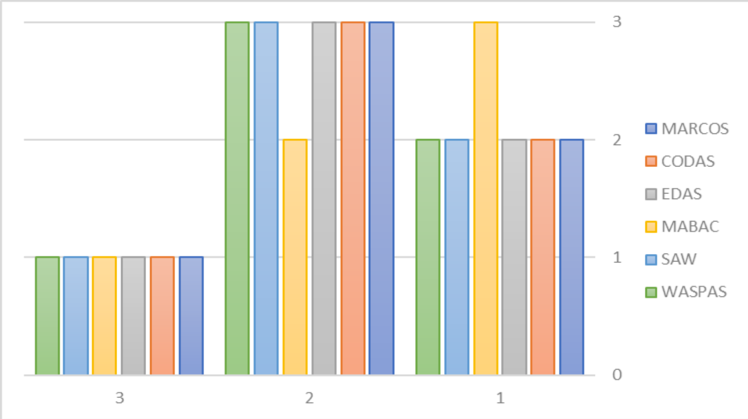

Figure 3. Results comparison

In addition to the comparative analysis, a further analysis was performed on the input parameters to validate the results. Using the equation (11) based on the most important criterion C1, simulated weights were calculated for 20 different scenarios (Set1-Set20) (Simić et al., 2020; Torkayesh et al., 2021).

$$w_{n\beta} = (1 - w_{n\alpha}) \frac{w_\beta}{(1 - w_n)} \tag{11}$$

In this formula, $w_{n\beta}$ represents the altered weights of the criteria, whereas $w_{n\alpha}$ represents the decreased weight of the most significant criterion. w_β represents the initial weight of each criterion, whereas w_n represents the original weight of the most important criterion. For C1, the most important criterion, the rate of reduction was decreased by 5% in each scenario, and the application was finalized through 20 scenarios. Figure 4 displays simulated weights for criteria.

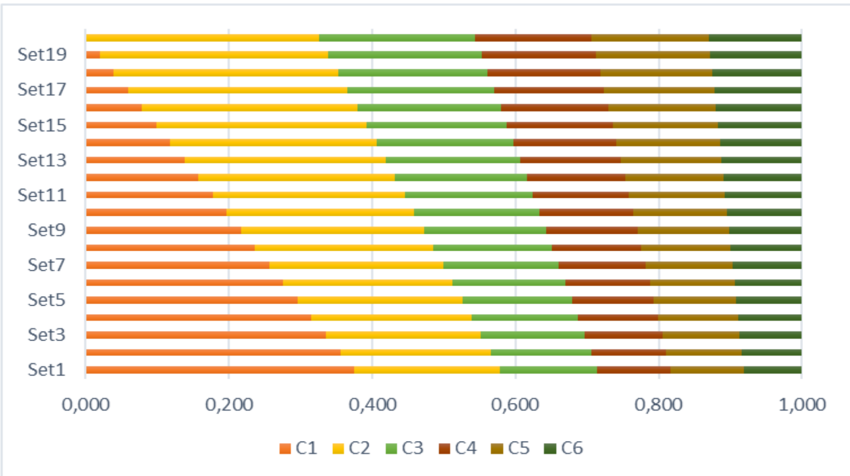

Figure 4. Criteria weights under 20 scenarios

Scenario-based rankings relying on simulated criteria weights are portrayed in Figure 5. Consequently, the ranking is sensitive to changes in the weighting of criteria. However, we can conclude that there is no dramatic change in scenario-based rankings. Although SPI-1 and SPI-2 share second and third ranks in various scenarios, SPI-3 is the most optimal solution in all cases. Overall, comparative analysis and sensitivity analysis based on simulated weights achieved a high level of consistency, thus yielding stability of the calculation.

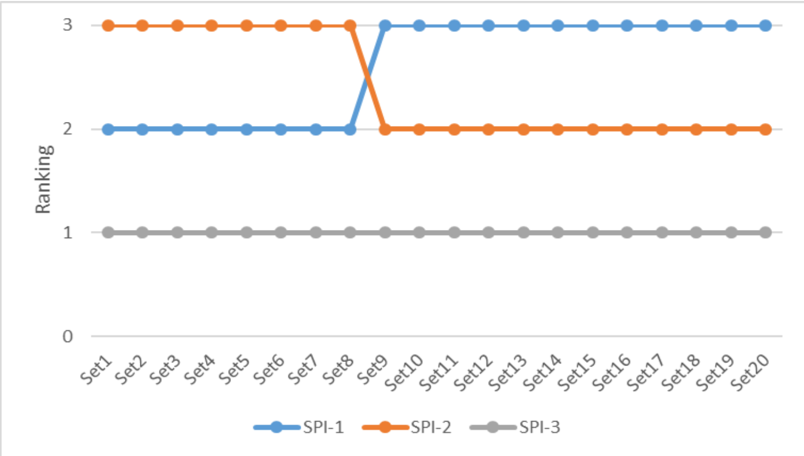

Figure 5. Scenario-based rankings through 20 scenarios

4. Conclusion

Green innovation has turned out to be a common and ordinally topic of interest all over the globe due to the increasing environmental concerns. However, growing industrialization, urbanization, globalization, and population have brought about various issues such as living conditions of social problems, economic problems, and damage to the environment. Through air pollution, industrialization has impacted air pollution through smoke and emissions caused by burning fossil fuels. The discharge contains carbon oxide that is a pollutant to the air. Water pollution stands as the second problem caused by industrialization. This is especially in areas where industries are established next to water bodies. The toxins from the water bodies contaminate the water bodies in a gaseous, liquid, and solid state. This normally happens if the industries direct their discharge to the water sources or contamination from landfills. Soil is also contaminated by industrial activities. Lead is a commonly known soil contaminant, although other hazardous and heavy metals can leach into the soil and destroy plants. Increased population, urbanization, industrialization, and others have resulted in dramatic environmental destruction. Forests are destroyed to acquire timber and give space for roads and industrial space.

Using MCDM models, the study attempted to evaluate and prioritize green innovation aspects in light of sustainability performance metrics. The use of the FUCOM-MARCOS method indicates that green managerial innovations are the utmost instrumental innovation bearing for industries' adoption in their manufacturing. The methodology has a tactical necessity in naturalizing green practices in manufacturing. Decision-makers can use this model to examine the green innovation exercises which will be of benefit in promoting social, economic, and environmental performance.

Although this paper attempts to add to the literature, it makes important suggestions for future research. As this study was limited to the textile industry in Nigeria, the results may not be generalizable. Therefore, future studies with similar analyses on leading textile exporters such as China, India, and Turkey can yield more generalizable results (World Trade Organization, 2021). Thus, the sustainable performance evaluation of the textile industry can better highlight the current global situation. Moreover, relying on aspects of green innovation, researchers can adapt this framework to other industries in Nigeria or any country. Although six green innovation aspects and three SPIs were employed in this study, future research may apply more comprehensive frameworks.

Finally, this study adopted an approach including FUCOM as a subjective weighting method and the MARCOS method as a ranking method. However, the MCDM literature has grown dramatically in the last few years. In this context, numerous new MCDM methods have been proposed for handling weighting and sorting problems (Ecer & Pamucar, 2022). In terms of the weighting procedure, objective weighting methods such as LOPCOW (Ecer & Pamucar, 2022) and MEREC (Keshavarz-Ghorabaee et al., 2021) and subjective weighting methods such as VIMM (Zakeri et al., 2021) and LBWA (Žižović & Pamučar, 2019) have emerged. Similarly, recent methods such as RAFSI (Žižović et al., 2020), RADERIA (Jakovljevic et al., 2021), LMAW (Pamučar et al., 2021), CoCoSo (Yazdani et al., 2019) and TRUST (Torkayesh & Deveci, 2021) have been proposed for ranking problems. The popular MCDM methods in the literature can be applied to the research problem of this study, and future research can evaluate the efficacy of the above-mentioned recent methods within this framework. Last but not least, qualitative expert opinions on matters such as aspects of green innovation are vague and ambiguous. In order to solve this issue, future research may adopt the fuzzy set theory. Therefore, researchers may reduce the level of ambiguity in a decision problem (Wang & Yang, 2021).

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