Revista de Administração Contemporânea
Journal of Contemporary Administration

ASSOCIAÇÃO NACIONAL DE PÓS-GRADUAÇÃO E PESQUISA EM ADMINISTRAÇÃO ANPAD

e-ISSN: 1982-7849

Methodological Article

A Hesitant Fuzzy Linguistic TOPSIS Model to Support Supplier Segmentation

Proposta de um Modelo Hesitant Fuzzy Linguistic TOPSIS para Segmentação de Fornecedores

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ABSTRACT

Objective: this study proposes a hesitant fuzzy linguistic TOPSIS model for supplier segmentation based on economic, environmental, and social criteria. **Proposal:** the model classifies suppliers in a segmentation matrix considering their capabilities and willingness to collaborate. It was implemented using Microsoft Excel© and applied to a hydropower plant. Two employees of the company chose a set of segmentation criteria, assigned weights to these criteria, and evaluated the performance of suppliers. In the pilot application, the performance of six suppliers was analyzed and ranked according to 28 criteria. The classification results were endorsed by the decision-makers involved. **Conclusion:** the model provides consistent results and can assist managers in designing development programs aimed at improving the economic, environmental, and social performance of suppliers. Additionally, it can support group decisions under uncertainty and hesitation, allows the use of linguistic expressions, and does not limit the amounts of criteria or alternatives.

Keywords: supplier segmentation, hesitant fuzzy linguistic TOPSIS, multicriteria decision-making.

RESUMO

Objetivo: este estudo propõe um modelo *hesitant fuzzy linguistic* TOPSIS para segmentação de fornecedores baseado em critérios econômicos, ambientais e sociais. **Proposta:** o modelo classifica os fornecedores em uma matriz de segmentação considerando suas capacidades e a disposição para colaborar. Foi implementado usando Microsoft Excel© e aplicado em uma usina hidrelétrica. Dois funcionários da empresa escolheram um conjunto de critérios de segmentação, atribuíram pesos a estes critérios e avaliaram o desempenho de alguns fornecedores. A aplicação-piloto permitiu analisar o desempenho de seis fornecedores e classificá-los de acordo com 28 critérios. Os resultados da classificação foram endossados pelos decisores envolvidos. **Conclusão:** o modelo apresenta resultados consistentes e pode auxiliar gestores na elaboração de programas de desenvolvimento visando a melhorar o desempenho econômico, ambiental e social dos fornecedores. Também é capaz de apoiar decisões em grupo sob incerteza e hesitação, habilita o uso de expressões linguísticas e não limita a quantidade de critérios e alternativas.

Palavras-chave: segmentação de fornecedores; *hesitant fuzzy linguistic* TOPSIS; decisão multicritério.

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Cite as: Borges, W. V., Lima, F. R., Junior, Peinado, J., & Carpinetti, L. C. R. (2022). A hesitant fuzzy linguistic TOPSIS model to support supplier segmentation. *Revista de Administração Contemporânea*, 26(6), e210133. https://doi.org/10.1590/1982-7849rac2022210133.en

Published as Early Access: December 10, 2021.
Assigned to this issue: June 06, 2022.

JEL Code: C6, Q0.

Editor-in-chief: Marcelo de Souza Bispo (Universidade Federal da Paraíba, PPGA, Brazil)
Associate Editor: Fernando Luiz Emerenciano Viana (Universidade de Fortaleza, Brazil)
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Peer Review Report: The Peer Review Report is available at this external URL.

Received: May 05, 2021
Last version received: September 09, 2021
Accepted: September 13, 2021

# of invited reviewers until the decision:

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1st round	x								
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INTRODUCTION

Demands from society, economic agents, and organizations increasingly encourage sustainable practices of energy and water efficiency, in addition to the control of carbon emissions (Jharkharia & Das, 2019). In this context, the concept of sustainable supply chain management (SSCM) has emerged, which considers that organizations must engage in activities that impact not only their economic development but also the environment and society (Osiro, Lima, & Carpinetti, 2018).

According to Seuring and Muller (2008), the SSCM concept refers to the "management of material and information flows as well as cooperation between organizations along the supply chain, integrating the triple bottom line selection factors that include all three sustainable development dimensions under consideration" (Seuring & Muller, 2008, p. 346). Triple bottom line (TBL) was developed by Elkington (2000) as a method for sustainability performance measurement. It can be characterized as an approach for performance management and evaluation that emphasizes the importance of economic, environmental, and social performance.

One of the main SSCM processes consists of supplier relationship management, which defines how a company interacts with its suppliers (Lambert & Schwieterman, 2012). Bemelmans, Voordijk, Vos e Buter (2012) explained that SSCM requires that suppliers are classified into categories to focus on the most important ones, set the correct priorities, and manage them according to their importance to the business.

In this context, the practice of supplier segmentation has been widely adopted by companies. This practice is essential for the success of supplier development programs, because by grouping suppliers according to their characteristics, it is possible to create coordinated actions aimed at efficiency gains (Lambert & Schwieterman, 2012). Day, Magnan and Moeller (2010) defined supplier segmentation as "a process that involves the division of suppliers into distinct groups, with different needs, characteristics, or behavior, requiring different types of relationship structures between companies in order to obtain exchange value" (Day, Magnan, & Moeller, 2010, p. 626). A tool called the segmentation matrix is often used in this process. It is composed of axes that represent a performance dimension considered important for the buyer (Santos, Osiro, & Lima, 2017). To classify the suppliers in each dimension, it is necessary to adopt a decision method that considers the contributions of multiple performance criteria and their weights (Akman, 2015).

Recent years have seen a significant increase in the amount of applications of multicriteria decision-making (MCDM) methods in the processes of segmentation, selection, and development of suppliers, as indicated by several systematic review studies on these topics (Borges & Lima, 2020; Guarnieri, 2015; Pedroso, Tate, Silva, & Carpinetti, 2021; Rashidi, Noorizadeh, Kannan, & Cullinane, 2020). Guarnieri (2015) analyzed 39 articles that presented decision models for supplier selection and found that fuzzy logic was adopted in 48% of these studies. Rashidi, Noorizadeh, Kannan and Cullinane (2020) reviewed 66 systematic review studies on sustainable supplier selection and concluded that techniques based on fuzzy logic are widely used, highlighting fuzzy-TOPSIS (technique for order preference by similarity to ideal solution) and fuzzy-AHP (analytic hierarchy process). In a systematic review study, Pedroso, Tate, Silva and Carpinetti (2021) mapped 88 articles and observed a significant growth in the number of publications on sustainable supplier development practices starting in 2015. They also identified the predominance of fuzzy logic among the studies in which MCDM and artificial-intelligence models were developed.

Borges and Lima (2020) conducted a systematic review that mapped 26 decision models for supplier segmentation and observed that the topic has been gaining attention in recent years, as 53.85% of the papers were published after 2016. These authors found that only the model proposed by Torres-Ruiz and Ravindran, which is based on the AHP technique, performs the segmentation based on economic, environmental, and social criteria. However, one of the limitations of this technique is related to the amount of input variables, which is limited by the human ability to perform the paired comparisons consistently (Lima, Osiro, & Carpinetti, 2014).

According to the bibliographical review conducted, there is no supplier segmentation model in the literature that supports group decisions in situations of uncertainty and hesitation. Pelissari, Oliveira, Abackerli, Ben-Amor, and Assumpção (2018) reported that uncertainty may result from the decision-maker's difficulty in expressing their knowledge about the problem, impacting the quality of the data resulting from their observations or measurements. The environment is also a source of uncertainty, in cases where data are difficult to obtain or verify. Although the models based on fuzzy logic are suitable for dealing with uncertainties, by allowing decision-makers to use linguistic terms (such as 'low' or 'high') to express their assessments, the fuzzy logic enables the decision-makers to choose only one linguistic term for each score or criterion weight evaluated (Osiro et al., 2018). In cases where the decision-maker hesitates in deciding between two terms and does not feel comfortable choosing a single term owing to the high level of uncertainty, the traditional fuzzy logic proves inadequate. It is more appropriate to use techniques based on hesitant fuzzy linguistic term sets, which are extensions of fuzzy logic proposed by Rodríguez, Martinez and Herrera (2012) to deal with decisions under hesitation.

One of these techniques is hesitant fuzzy linguistic TOPSIS (HFL-TOPSIS), which deals with group decisions under hesitation by allowing the simultaneous use of multiple linguistic terms and the use of linguistic expressions (such as 'between low and medium'), bringing greater flexibility to decision-makers (Beg & Rashid, 2013). Despite its potential to circumvent the limitations of previous models regarding the support in situations of hesitation and the maximum number of alternatives and suppliers, no studies were found in which this technique was applied to the segmentation of suppliers.

Given the above background, the objective of this study was to propose an HFL-TOPSIS model for supplier segmentation based on economic, environmental, and social criteria. The model was applied to real data provided by employees of a hydroelectric power plant. This application involved the evaluation of six suppliers considering economic, environmental, and social criteria. The remainder of this article is organized as follows. The second section discusses the literature on models for supplier segmentation. The third section describes the methodological procedures. The fourth section presents and discusses the results of the application. The fifth section presents the results of the sensitivity analysis. The sixth section concludes the paper.

THEORETICAL FRAMEWORK

Decision models for supplier segmentation

Supplier segmentation is theoretically based on the established fundamentals of market segmentation practice. From the perspective of the supplier, the most popular tool for supplier categorization is called the portfolio matrix. These matrices are composed of segmentation dimensions, which are directly related to a set of criteria on which suppliers will be evaluated (Osiro, Lima, & Carpinetti, 2014; Park, Shin, Chang, & Park, 2010).

Various decision support models for supplier segmentation are reported in the literature, such as those based on MCDM and artificial-intelligence techniques. The purposes of using these models include the definition of the type of relationship to be developed, the identification of suppliers that require development programs, and the analysis of similarities and inconsistencies within each group of suppliers (Bianchini, Benci, Pellgrini, & Rossi, 2019; Rezaei, Kadzinski, Vana, & Tavasszy, 2017).

Through the literature survey conducted in this study, several supplier segmentation models and two systematic review studies were identified, which reinforces the relevance of this topic. Day et al. (2010) reviewed dozens of approaches to support the segmentation, classifying them and creating a relevant taxonomy. While Day et al. (2010) mainly analyzed conceptual models and focused on the mapping of structural elements of the studies, the review conducted by Borges and Lima (2020) presented a mapping of 26 quantitative models for supplier segmentation.

Table 1 presents a list of models for supplier segmentation. This table was constructed by the authors of this study from information presented by Borges and Lima (2020). The model of Kaur and Sing (2021), which was identified during the survey conducted by the authors of this study, is included. Table 1 highlights the decision methods and dimensions employed in the segmentation matrices. The most widely used method was AHP, with eight applications, followed by fuzzy c-means, with four applications. Although a wide variety of segmentation dimensions can be adopted, the most widely used are 'supplier capabilities' and 'willingness to collaborate.' Only the model proposed by Torres-Ruiz and Ravindran (2018) performs the segmentation of suppliers considering criteria associated with the three dimensions of TBL. While most models consider only economic criteria, such as the price and financial situation of the supplier, six models focus on environmental criteria (Akman, 2015; Bai, Rezaei, & Sarkis, 2017; Demir, Akpinar, Araz, & Ilgin, 2018; Jharkharia & Das, 2019; Rezaei et al., 2017), such as proper waste disposal and energy efficiency. In this regard, it is noted that social criteria, such as child labor and health programs for employees, have been neglected by previous models.

Table 1. Methods and dimensions used in supplier segmentation models.

		Author(s)
Method(s)	AHP	Bianchini, Benci, Pellgrini and Rossi (2019), Park, Shin, Chang and Park (2010), Torres-Ruiz and Ravindran (2018)
	AHP and fuzzy 2-tuple	Santos, Osiro and Lima (2017)
	AHP and fuzzy relations	Rezaei and Ortt (2013b)
	AHP, fuzzy c-means and VIKOR	Akman (2015)
	AHP, K-means and simulated annealing algorithm	Che (2011)
	AHP, PROMETHÉE and MAUT	Segura and Maroto (2017)
	Best-worst method	Rezaei and Lajimi (2019), Rezaei, Wang, and Tavasszy (2015)
	DEA	Restrepo and Villegas (2019)
	DEMATEL	Parkouhi, Ghadikolaei, and Lajimi (2019)
	ELECTRE TRI	Rezaei et al. (2017)
	Fuzzy-AHP	Lo and Sudjatmika (2015)
	Fuzzy-AHP and fuzzy c-means	Haghighi, Morad and Salahi (2014)
	Fuzzy c-means and fuzzy formal concept analysis	Jharkharia and Das (2019)
	Fuzzy-TOPSIS	Lima and Carpinetti (2016), Medeiros and Ferreira (2018)
	Fuzzy inference	Aloini, Dulmin, Mininno and Zerbino (2019), Osiro, Lima and Carpinetti (2014), Rezaei and Ortt (2013a)
	PROMETHÉE	Boujelben (2017)
	RST, VIKOR and fuzzy c-means	Bai, Rezaei and Sarkis (2017)
	VIKORSORT	Demir, Akpinar, Araz and Ilgin (2018)
Segmentation dimensions	Supplier attractiveness and strength of relationship	Aloini et al. (2019)
	Supplier capabilities and supplier willingness to collaborate	Bai et al. (2017), Boujelben (2017), Haghighi et al. (2014), Lo and Sudjatmika (2015), Rezaei and Ortt (2013a), Rezaei and Ortt (2013b), Rezaei, Kadzinski, Vana and Tavasszy (2017), Rezaei et al. (2015), Santos et al. (2017)
	Cost and delivery performance	Lima and Carpinetti (2016)
	Supplier investment decisions and supplier collaboration decisions	Jharkharia and Das (2019)
	Critical and strategic	Segura and Maroto (2017)
	Diversity efficiency and cross efficiency	Restrepo and Villegas (2019)
	Strategic importance and relationship attractiveness	Park, Shin, Chang and Park (2010)
	Resiliency enhancer and resiliency reducer	Parkouhi et al. (2019)
	Country, supplier business performance, and supplier E&S	Torres-Ruiz and Ravindran (2018)
	Potential for partnership and delivery performance	Osiro et al. (2014)
	Supply risk and impact on profit	Bianchini et al. (2019), Medeiros and Ferreira (2018)
	Supply risk, profit impact, capabilities, and willingness to collaborate	Rezaei and Lajimi (2019)

Note. Adapted from Borges and Lima (2020).

Although the models presented in Table 1 have provided several theoretical and practical contributions in the supplier segmentation field, they have limitations arising from the characteristics of the decision techniques adopted. Although most are adequate for uncertainty scenarios and some of the fuzzy models allow the use of linguistic terms by decision-makers, none of the models found are adequate for hesitation situations, where decision-makers are uncertain in the choice of terms and therefore prefer to express their assessments in the form of linguistic expressions. The HFL-TOPSIS method, which until 2021 had not been applied to supplier segmentation, may help circumvent these limitations.

METHODOLOGICAL PROCEDURES

This study can be characterized as descriptive axiomatic quantitative research based on modeling and simulation, as a quantitative model is developed for supplier segmentation. The normative axiomatic research is characterized by obtaining solutions within the defined model and ensuring that these solutions provide insights into the structure of the problem (Bertrand & Fransoo, 2002).

The research stages were as follows: bibliographic research, modeling, application, and sensitivity analysis. The bibliographical research involved the collection of articles in major databases on the topic (Science Direct; Springer; Scopus; Emerald Insight; IEEE Xplore®; Taylor & Francis; and Wiley), using combinations of the terms 'supplier segmentation,' 'decision models,' 'multicriteria decision-making,' 'supplier relationship management,' and 'sustainable supply chain management,' among others. This bibliographical research subsidized the delineation of the research gap and the development of the proposed model.

The modeling stage was initiated by developing a conceptual model for supplier segmentation based on the segmentation matrix proposed by Rezaei and Ortt (2013a) and the HFL-TOPSIS method (Beg & Rashid, 2013; Magalhães, 2020). The HFL-TOPSIS method was developed by Beg and Rashid (2013) and uses hesitant fuzzy linguistic term sets (HFLTS) in combination with TOPSIS principles. The steps of HFL-TOPSIS are detailed as follows.

Let $\tilde{X}^l = \left[H^l_{Sij}\right]_{mxn}$ be a fuzzy decision matrix; $E = \{e_1, e_2, \dots, e_k\}$ is the set of involved decision-makers, $A = \{A_1, A_2, \dots, A_m\}$ is the set of alternatives, and $C = \{C_1, C_2, \dots, C_n\}$ is the set of criteria used to evaluate the alternatives. The performance of the alternative A_i in relation to the criterion C_j is denoted as x_{ij}. The aggregate decision matrix $X = [x_{ij}]$, with $X_{ij} = [S_{pij}, S_{qij}]$, is computed considering the different opinions of the decision-makers $(\tilde{X}^1, \tilde{X}^2, \dots, \tilde{X}^k)$, according to equations 1 and 2 (Beg & Rashid, 2013).

$$s_{pij} = \min\left\{\min_{l=1}^{k}\left(\max H^l_{Sij}\right), \max_{l=1}^{k}\left(\min H^l_{Sij}\right)\right\} \tag{1}$$

$$s_{qij} = \max\left\{\min_{l=1}^{k}\left(\max H^l_{Sij}\right), \max_{l=1}^{k}\left(\min H^l_{Sij}\right)\right\} \tag{2}$$

Let Ω_b be a collection of benefit criteria (i.e., higher score on C_j corresponds to a higher overall score) and Ω_c be a collection of cost criteria (lower score on C_j corresponds to a higher final score). The positive ideal solution (PIS) is represented as $\tilde{A}^+ = (\tilde{V}_1^+, \tilde{V}_2^+ \dots, \tilde{V}_n^+)$, and the negative ideal solution (NIS) is represented as $\tilde{A}^- = (\tilde{V}_1^-, \tilde{V}_2^- \dots, \tilde{V}_n^-)$. Equations 3 and 4 guide the composition of PIS and NIS for benefit and cost criteria. In these equations, $\tilde{V}_j^+ = [v_{pj}, v_{qj}]$ with $(j = 1, 2, \dots, n)$ and $(i = 1, 2, \dots, m)$ (Beg & Rashid, 2013).

$$\tilde{A}^+ = \left[\left(\left(\max_{l=1}^{k}\left(\max_i H^l_{Sij}\right)\right)\middle| j \in \Omega_b, \left(\min_{l=1}^{k}\left(\min_i H^l_{Sij}\right)\right)\middle| j \in \Omega_c\right), \left(\left(\max_{l=1}^{k}\left(\max_i H^l_{Sij}\right)\right)\middle| j \in \Omega_b, \left(\min_{l=1}^{k}\left(\min_i H^l_{Sij}\right)\right)\middle| j \in \Omega_c\right)\right] \tag{3}$$

$$\tilde{A}^- = \left[\left(\left(\min_{l=1}^{k}\left(\min_i H^l_{Sij}\right)\right)\middle| j \in \Omega_b, \left(\max_{l=1}^{k}\left(\max_i H^l_{Sij}\right)\right)\middle| j \in \Omega_c\right), \left(\left(\min_{l=1}^{k}\left(\min_i H^l_{Sij}\right)\right) | j \in \Omega_b, \left(\max_{l=1}^{k}\left(\max_i H^l_{Sij}\right)\right) | j \in \Omega_c\right)\right] \tag{4}$$

After aggregating the matrices and obtaining the ideal solutions, a positive ideal separation matrix (D^+) and a negative ideal separation matrix (D^-) are obtained using equations 5 and 6. Each element of these matrices is calculated using equation 7, in which p and q represent the limits of the envelope of H_S^1, and p' and q' are the boundaries of the envelope of H_S^2 (Beg & Rashid, 2013).

$$D^+ = \begin{pmatrix} d(x_{11}, \tilde{V}_1^+) & + & d(x_{12}, \tilde{V}_2^+) + & \cdots & + \, d(x_{1n}, \tilde{V}_n^+) \\ d(x_{21}, \tilde{V}_1^+) & + & d(x_{22}, \tilde{V}_2^+) + & \cdots & + \, d(x_{2n}, \tilde{V}_n^+) \\ \vdots & & \vdots & \vdots & + \quad \vdots \\ d(x_{m1}, \tilde{V}_1^+) & + & d(x_{m2}, \tilde{V}_2^+) + & \cdots & + \, d(x_{mn}, \tilde{V}_n^+) \end{pmatrix} \tag{5}$$

$$D^- = \begin{pmatrix} d(x_{11}, \tilde{V}_1^-) & + & d(x_{12}, \tilde{V}_2^-) + & \cdots & + \, d(x_{1n}, \tilde{V}_n^-) \\ d(x_{21}, \tilde{V}_1^-) & + & d(x_{22}, \tilde{V}_2^-) + & \cdots & + \, d(x_{2n}, \tilde{V}_n^-) \\ \vdots & & \vdots & \vdots & + \quad \vdots \\ d(x_{m1}, \tilde{V}_1^-) & + & d(x_{m2}, \tilde{V}_2^-) + & \cdots & + \, d(x_{mn}, \tilde{V}_n^-) \end{pmatrix} \tag{6}$$

$$d\left(H_S^1, H_S^2\right) = |q' - q| + |p' - p| \tag{7}$$

Finally, we calculate the relative closeness (RC) of each alternative using equation 8, in which $D_i^- = \sum_{j=1}^{n} d(x_{ij}, \tilde{V}_j^-)$ e $D_i^+ = \sum_{j=1}^{n} d(x_{ij}, \tilde{V}_j^+)$.

A higher value of $RC(A_i)$ corresponds to better overall performance A_i (Beg & Rashid, 2013).

$$RC(A_i) = \frac{D_i^-}{D_i^+ + D_i^-} \quad (8)$$

The HFL-TOPSIS method was chosen because it does not restrict the quantity of input variables, offering support to group decisions and under hesitation. It was also chosen because it is a compensatory method, as the focus of the segmentation is to evaluate the overall performance considering the contribution of all criteria, instead of eliminating the suppliers that do not satisfy certain criteria, as occurs in the selection stage. However, the original version of this technique does not enable the decision-maker to assign weights to criteria, which is essential in segmentation for incorporating the strategic intentions of the buyer into the model, and generate results that reflect these preferences. For instance, by assigning different weights to the criteria, it is possible to define whether the buyer wishes to prioritize cost reduction or the improvement of reliability and agility in supplier deliveries, as well as to distinguish which criteria more significantly impacts the overall performance of the supplier.

To enable the assignment of weights to criteria, an adapted version of HFL-TOPSIS was adopted, which was proposed by Magalhães (2020) and applies the algorithm of Beg and Rashid (2013) with minor changes. When this approach is applied for the evaluation of weights, each row of the matrix represents a criterion, and each column represents a decision-maker. In the alternative evaluation step, the normalized values of the weights (*CNi*) are used to weight the scores of the alternatives during the calculation of the distances (Onar, Oztaysi, & Kahraman, 2014), which is performed using equations 9 to 11, where h_j^* and h_j^- represent the elements of the PIS and NIS, respectively. Equation 11 gives the distance between two hesitant fuzzy sets, considering each of the linguistic terms $h_{\sigma(j)}$ that compose these sets, where l represents the number of elements in the lager set (Magalhães, 2020).

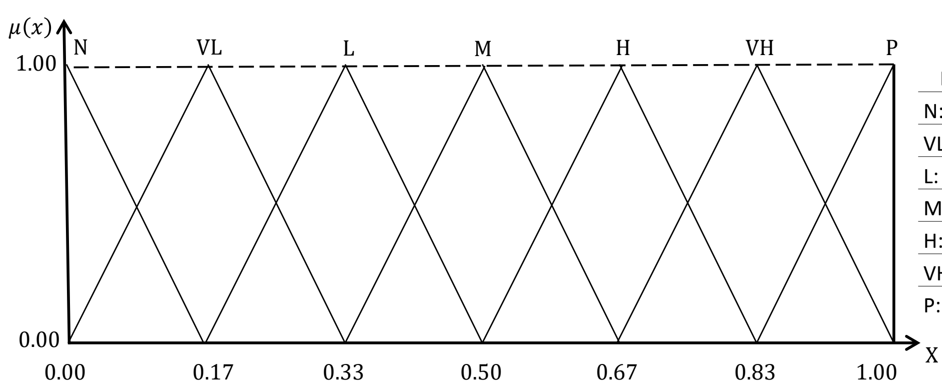
$$D_i^+ = \sum_{j=1}^{n} w_j \left\| h_{ij} - h_j^+ \right\| \quad (9)$$

$$D_i^- = \sum_{j=1}^{n} w_j \left\| h_{ij} - h_j^- \right\| \quad (10)$$

$$\left\| h_{ij} - h_j \right\| = \frac{1}{l} \sum_{j=1}^{l} \left| h_{1\sigma(j)} - h_{2\sigma(j)} \right| \quad (11)$$

A computational model based on the equations 1 to 11 was implemented using MS Excel© software. This tool was selected because it is widely used in business environments and provides a simple and transparent implementation. The model application was based on linguistic judgments provided by two employees of the purchasing department of a hydroelectric power plant (decision-maker 1 and decision-maker 2). This company had a broad supply base, and the interviewed decision-makers had knowledge regarding the performance of the analyzed suppliers. The decision-makers selected the criteria, assigned their weights, evaluated the suppliers, and analyzed the results. Data were collected using a simple form, which contained the research objective, the possible criteria, and a space reserved for the evaluation of criteria and alternatives. The collection was conducted via videoconference, and the data were tabulated in an electronic spreadsheet. The criteria selection was based on a list extracted from the works of Rezaei and Ortt (2013a), Osiro et al. (2018) and Torres-Ruiz and Ravindran (2018).

Regarding the definition of the linguistic scales for performing the assessments, the decision-makers chose the scale proposed by Rodríguez et al. (2012), which is presented in Figure 1. The figure shows the label of each linguistic term (S_i) and the vertices of the corresponding triangular sets. This scale was selected because it contains seven terms and provides a more thorough evaluation than a scale with fewer terms. The decision-makers selected a single scale for the evaluation of criteria and alternatives, as they considered that the scale shown in Figure 1 would be adequate for this purpose. Additionally, the use of a single scale simplified the application.



Linguistic terms (S_i)	Vertices
N: Nothing (S_0)	(0; 0; 0.17)
VL: Very Low (S_1)	(0; 0.17; 0.33)
L: Low (S_2)	(0.17; 0.33; 0.50)
M: Medium (S_3)	(0.33; 0.50; 0.67)
H: High (S_4)	(0.50; 0.67; 0.83)
VH: Very High (S_5)	(0.67; 0.83; 1)
P: Perfect (S_6)	(0.83; 1; 1)

Figure 1. Linguistic scale defined for the evaluation of criteria and alternatives.

The linguistic terms and linguistic expressions were converted to the HFLTS format, as described by Rodríguez et al. (2012). The conversion of the linguistic terms to HFLTS was based on the indices (i = 0, …, 6) of the linguistic terms shown in Figure 1, i.e., S_0 = N, S_1 = MB, S_2 = B, S_3 = M, S_4 = H, S_5 = VH, and S_6 = AB. For example, by converting the weight of C_2 ('between low and medium') given by decision-maker 1, we obtain [L, M], which results in the envelope [2, 3]. In the HFLTS approach, only the values of the envelope boundaries are used in the calculations, in contrast to traditional fuzzy techniques that use the values of the degrees of pertinence or vertices of the fuzzy numbers.

After the application, a sensitivity analysis was conducted to test the effect of the criteria weight variation on the supplier categorization considering three distinct scenarios, which are detailed in the Results and Discussion section.

RESULTS AND DISCUSSION

The proposed model has three stages and was developed based on the works of Rodríguez et al. (2012), Beg and Rashid (2013), Rezaei and Ortt (2013a) and Osiro, Lima and Carpinetti (2018). This model aims to assist managers in the supplier segmentation process based on the TBL criteria, which are associated with the segmentation dimensions called 'suppliers' capabilities' and 'suppliers' willingness to collaborate' proposed by Rezaei and Ortt (2013a). This segmentation approach was chosen because of its easy adaptability in relating the sustainability criteria with the segmentation dimensions. It is the most widely used approach in applications aimed at the preparation of supplier development programs. Suppliers are grouped according to their performance, in contrast to other approaches, where suppliers are grouped according to the items that they supply (Medeiros & Ferreira, 2018; Park et al., 2010).

Figure 2 presents the steps of each stage of the proposed model. Stage 1 consists of the definition and evaluation of the criteria weights. This stage begins with the assembly of the team responsible for decision-making. It is recommended to select professionals who are involved with the purchasing process of the company, as well as other areas related to supply management, such as quality, environmental, and logistics management. Once the decision-makers are defined, they must choose the TBL criteria associated with the suppliers' evaluation concerning the dimensions 'capabilities' and 'willingness to collaborate.' Next, they must define a linguistic scale to assess the importance of these criteria and perform the evaluations. Then, the criteria weights are calculated using the HFL-TOPSIS technique (Beg & Rashid, 2013; Magalhães, 2020).

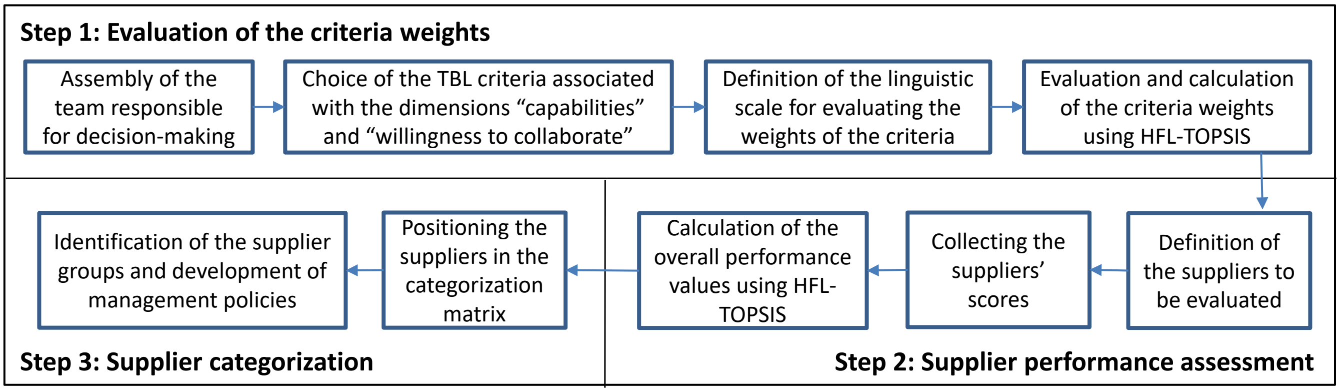


Figure 2. Proposed model for supplier segmentation.
Proposed by the authors.

Step 2 begins with defining which suppliers will be evaluated by the team of decision-makers. Subsequently, the language scale is defined for the evaluation of the suppliers' scores, and the scores are collected for the criteria of both dimensions. The equations of Beg and Rashid (2013) are used to calculate the overall performance of the suppliers in each dimension.

Finally, step 3 consists of categorizing suppliers. The suppliers are positioned in the categorization matrix according to the overall performance of each supplier for each segmentation dimension. To allow better data visualization, equation 12 is applied to perform a sigmoidal normalization, as described by Osiro et al. (2018). In this equation, v_n represents the normalized value, and v represents the original value. $\bar{v}$ represents the mean, and σ_v represents the standard deviation (referring to the original values).

$$v_n = \frac{1}{1+e^{-\frac{v-\bar{v}}{\sigma_v}}} \quad (12)$$

Once the segmentation matrix is assembled, it is possible to identify the groups to which suppliers belong according to the quadrants in which they are positioned. This positioning of suppliers in the matrix is important because it provides the basis for supplier development programs. The programs formulated should provide the displacement of suppliers to the quadrant located in the upper part and to the right of the matrix (Rezaei & Ortt, 2013a). The following section presents a real application of the proposed model to test it and demonstrate its use.

Application

The application was performed in a hydroelectric plant located in Rio Grande in the state of São Paulo. The plant has an installed capacity of 210 MW, provided by five bulb-type generator units. Its reservoir covers municipalities located in the states of São Paulo and Minas Gerais.

Step 1: definition and evaluation of criteria weights

Stage 1 began with the assembly of the team of decision-makers, which comprised two employees responsible for purchasing. The decision-makers jointly chose the criteria from a list extracted from the literature, covering the three TBL dimensions. The choice was based on the principles of the company: 'dam safety, technology, and innovation.' The criteria chosen for the 'willingness to collaborate' dimension are presented in Table 2. Among them, C_7 and C_9 as well as C_{11}, C_{14} and C_{15} of the 'capabilities' dimension, are related to safety (Table 4). C_2, C_4 and C_5 as well as C_5, C_6, C_7 and C_{18} of the 'capabilities' dimension, are related to technology and innovation. C_1, C_2 and C_3 are aligned with the solid waste management and environmental education programs developed by the plant. Most of the other criteria are related to quality management practices and company operations. Only benefit criteria were selected; i.e., higher supplier performance in the criterion corresponds to higher overall performance.

Table 2. Linguistic judgments for the weights of the criteria of the 'willingness to cooperate' dimension.

Chosen criteria	Decision-maker 1		Decision-maker 2	
	Judgments	Conversion	Judgments	Conversion
C_1: Effort to reduce material waste	Between very low and low	[VL,L]	Between medium and high	[M,H]
C_2: Ability to work in a team	Between low and medium	[L,M]	Between medium and high	[M,H]
C_3: Commitment to quality	Between medium and high	[M,H]	Between medium and high	[M,H]
C_4: Willingness to share information, ideas, technology, and cost savings	Between very low and low	[VL,L]	Between medium and high	[M,H]
C_5: Long-term relationship	Between low and medium	[L,M]	Between medium and high	[M,H]
C_6: Honesty	Between medium and high	[M,H]	Between high and very high	[H,VH]
C_7: Safety auditorship	Between medium and high	[M,H]	Perfect	[P]
C_8: Ease of communication	Between very low and low	[VL,L]	Between medium and high	[M,H]
C_9: Compliance procedures	Between medium and high	[M,H]	Perfect	[P]

Note. Proposed by the authors.

Subsequently, the decision-makers individually evaluated the criteria weights using the scale of Figure 1. Table 2 presents the linguistic terms and expressions assigned by each decision-maker, as well as the result of the conversion of these judgments into the HFLTS format. By utilizing the envelopes of these sets, which were defined according to the *i*-indexes of the linguistic terms, the computational model calculation sequence was conducted. First, the weights of the criteria of the 'willingness to collaborate' dimension were calculated. The HFLTS envelope values concerning the aggregate judgments of the decision-makers are presented in Table 3, which were produced using equations 1 and 2. Values are represented by S_p and S_q, where p and q represent the envelope lower limit index and upper limit index, respectively, which may vary from zero to six. The value zero corresponds to the judgment 'nothing,' one corresponds to 'very low,' and so on.

Table 3. Calculation of the weights of the criteria of the 'willingness to collaborate' dimension.

Criteria	S_p	S_q	$d(H_S^1, H_S^2)$		D^+	$d(H_S^1, H_S^2)$		D^-	CC_i	CC_i normalized
C_1	2	3	3	4	7	1	1	2	0.222	0.057
C_2	3	3	3	3	6	1	2	3	0.333	0.086
C_3	3	4	2	3	5	2	2	4	0.444	0.114
C_4	2	3	3	4	7	1	1	2	0.222	0.057
C_5	3	3	3	3	6	1	2	3	0.333	0.086
C_6	4	4	2	2	4	2	3	5	0.556	0.143
C_7	4	6	0	2	2	4	3	7	0.778	0.200
C_8	2	3	3	4	7	1	1	2	0.222	0.057
C_9	4	6	0	2	2	4	3	7	0.778	0.200

Note. Proposed by the authors.

The NIS was obtained using equation 4, equating to $\tilde{A}^- = [1, 2]$. The PIS defined by equation 3 was $\tilde{A}^+ = [6, 6]$. The distances between the scores of each alternative in relation to each value of NIS and PIS were obtained using equations 5 to 7, resulting in D^- and D^+. The relative proximity coefficients (CC_i) were calculated using equation 8. Subsequently, they were normalized with the objective of ensuring that the sum of the weights was equal to one; all the values were divided by the largest value (0.778), to satisfy the premise of equations 9 and 10. The results are presented in Table 3.

Table 4 presents criteria selected by decision-makers for the 'capabilities' dimension, together with the judgments attributed to the weights and the conversion of these into HFLTS. The previously applied sequence of calculations (equations 1 to 8) was replicated for these judgments. The CC_i and normalized CC_i values for the criteria weights of the 'capabilities' dimension are presented in Table 5.

Table 4. Linguistic judgments for the criteria of the 'capabilities' dimension.

Chosen criteria	Decision-maker 1		Decision-maker 2	
	Judgments	Conversion	Judgments	Conversion
C_1: Environmental certifications	Between high and very high	[M,H]	Between medium and high	[M,H]
C_2: Proper waste disposal	Between medium and high	[P]	Between medium and high	[M,H]
C_3: Disposal of hazardous materials	Between medium and high	[M,H]	Between medium and high	[M,H]
C_4: On-time shipment	Between medium and high	[M,H]	Between high and very high	[H,VH]
C_5: Technological capability	Between high and very high	[VL,L]	Between high and very high	[H,VH]
C_6: Quick problem solving	Between medium and high	[L,M]	Between high and very high	[H,VH]
C_7: Technical knowledge	Perfect	[M,H]	Between high and very high	[H,VH]
C_8: Productivity and efficiency	Between medium and high	[M,H]	Between high and very high	[H,VH]
C_9: Quality	Between medium and high	[H,VH]	Between high and very high	[H,VH]
C_{10}: Average training time per employee	Between very low and low	[P]	Between low and medium	[L,M]
C_{11}: Employees' healthcare	Between low and medium	[M,H]	Between medium and high	[M,H]
C_{12}: Child labor	Between medium and high	[H,VH]	Between very low and low	[VL,L]
C_{13}: Work conditions	Between medium and high	[M,H]	Between medium and high	[M,H]
C_{14}: Safety training	Between high and very high	[M,H]	Perfect	[P]
C_{15}: Number of accidents	Perfect	[AB]	Between high and very high	[H,VH]
C_{16}: Employee satisfaction	Between medium and high	[M,A]	Between medium and high	[M,H]
C_{17}: Company reputation	Between high and very high	[A,MA]	Between medium and high	[M,H]
C_{18}: Technical structure	Between medium and high	[M,A]	Between medium and high	[M,H]
C_{19}: Financial situation	Between medium and high	[M,A]	Between low and medium	[L,M]

Note. Proposed by the authors.

Table 5. Weights of the criteria for the 'capabilities' dimension.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
CC_i	0.556	0.444	0.444	0.556	0.667	0.556	0.889	0.556	0.556	0.111
CC_i normalized	0.056	0.045	0.045	0.056	0.067	0.056	0.09	0.056	0.056	0.011
	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	
CC_i	0.333	0.222	0.444	0.889	0.889	0.444	0.556	0.444	0.333	
CC_i normalized	0.034	0.022	0.045	0.09	0.09	0.045	0.056	0.045	0.034	

Note. Proposed by the authors.

Step 2: assessment of supplier performance

This stage began with the choice of six suppliers to be evaluated by the decision-makers, from the supply base of the purchasing company. To maintain confidentiality of their identities, these suppliers were labeled as F_1, F_2, F_3, F_4, F_5 and F_6. The evaluation of their performance in relation to the 28 criteria was based on the linguistic scale used in the previous step, which is presented in Figure 1. Initially, the decision-makers assigned judgments for the suppliers' performance regarding the criteria of the 'willingness to collaborate' dimension using linguistic terms and expressions. Table 6 presents these judgments converted into the HFLTS format.

Table 6. Supplier evaluation regarding the criteria of the 'willingness to collaborate' dimension.

C_i	Decision-maker 1						Decision-maker 2					
	F_1	F_2	F_3	F_4	F_5	F_6	F_1	F_2	F_3	F_4	F_5	F_6
C_1	[M,H]	[H]	[M,H]	[M,H]	[M,H]	[L,M]	[L]	[H,VH]	[L]	[L,M,H]	[M,H]	[M,H]
C_2	[M,H]	[H]	[M,H]	[M,H]	[M,H]	[M,H]	[L,M]	[H,VH]	[M]	[M,H]	[H,VH]	[M,H]
C_3	[M,H]	[H,VH]	[M,H]	[M,H]	[M,H]	[L,M]	[L]	[H,VH]	[L,M]	[M,H]	[M,H]	[M,H]
C_4	[L]	[L,M]	[VL,L]	[L,M]	[L,M]	[VL,L]	[M,H]	[M,H]	[L]	[M,H]	[M,H]	[H,VH]
C_5	[L,M]	[H,VH]	[M,H]	[M,H]	[H,VH]	[M,H]	[L,M]	[P]	[L,M]	[H,VH]	[H,VH]	[P]
C_6	[L,M]	[H,VH]	[L,M]	[M,H]	[M,H]	[M,H]	[H]	[P]	[H,VH]	[H,VH]	[P]	[P]
C_7	[M]	[H,VH]	[M,H]	[M,H]	[M,H]	[M,H]	[P]	[P]	[H,VH]	[M,H]	[M,H]	[P]
C_8	[L,M]	[M,H]	[M,H]	[M,H]	[M,H]	[L,M]	[L,M]	[P]	[L,M]	[H,VH]	[H,VH]	[L,M]
C_9	[M,H]	[M,H]	[M,H]	[M,H]	[M,H]	[M,H]	[P]	[P]	[P]	[P]	[P]	[P]

Note. Proposed by the authors.

According to the data shown in Table 6, a spreadsheet containing the HFLTS envelopes $[S_p, S_q]$ referring to the values of the judgments was assembled. These values were aggregated using equations 1 and 2, and the results are presented in Table 7. Next, the PIS and NIS were defined by applying equations 3 and 4, respectively. These equations returned the following results: A^+ = ([4,5]; [4,5]; [4,5]; [4,5]; [6,6]; [6,6]; [6,6]; [6,6]; [6,6]) and A^- = ([2,2]; [2,3]; [2,2]; [1,2]; [2,3]; [2,3]; [3,3]; [2,3]; [3,4]). The distances between the aggregate values of the judgments and the ideal solutions were calculated. For this, equations 9 to 11 were used, which allowed the scores to be weighted according to the weights calculated in the previous step (CN_i). The results of the distance calculations are presented in Table 8.

The values of RC_i were calculated using equation 8, followed by the application of equation 12 for sigmoidal normalization. The results are presented in Table 9. In this table, a higher score corresponds to better global performance of the supplier.

For the 'capabilities' dimension, the same procedures used to calculate the suppliers' scores in the 'willingness to collaborate' dimension were employed. Table 10 presents the judgments collected from the decision-makers based on the scale presented in Figure 1, converted into the HFLTS format. Next, equations 1 to 4 and 9 to 12 were applied, yielding the values of the suppliers' global performance (RC_i) in the 'capabilities' dimension. The final results are presented in Table 11.

Table 7. Aggregate values of the assessments for the 'willingness to collaborate' dimension.

C_i	F_1	F_2	F_3	F_4	F_5	F_6
C_1	[2, 3]	[4, 4]	[2, 3]	[3, 4]	[3, 4]	[3, 3]
C_2	[3, 3]	[4, 4]	[3, 3]	[3, 4]	[4, 4]	[3, 4]
C_3	[2, 3]	[4, 5]	[3, 3]	[3, 4]	[3, 4]	[3, 3]
C_4	[2, 3]	[3, 3]	[2, 2]	[3, 3]	[3, 3]	[2, 4]
C_5	[2, 3]	[5, 6]	[3, 3]	[4, 4]	[4, 5]	[4, 6]
C_6	[3, 4]	[5, 6]	[3, 4]	[4, 4]	[4, 6]	[4, 6]
C_7	[3, 6]	[5, 6]	[4, 4]	[3, 4]	[3, 4]	[4, 6]
C_8	[2, 3]	[4, 6]	[3, 3]	[4, 4]	[4, 4]	[2, 3]
C_9	[4, 6]	[5, 6]	[4, 6]	[4, 6]	[4, 6]	[4, 6]

Note. Proposed by the authors.

Table 8. Distances of the values of the alternatives from the ideal solutions.

C_i	Distances from the PIS $\left\| \|h_{ij} - h_j^{+}\| \right\|$						C_i	Distances from the NIS $\left\| \|h_{ij} - h_j^{-}\| \right\|$					
	F_1	F_2	F_3	F_4	F_5	F_6		F_1	F_2	F_3	F_4	F_5	F_6
C_1	0.114	0.029	0.114	0.057	0.057	0.086	C_1	0.029	0.114	0.029	0.086	0.086	0.057
C_2	0.129	0.043	0.129	0.086	0.043	0.086	C_2	0.043	0.129	0.043	0.086	0.129	0.086
C_3	0.229	0.000	0.171	0.114	0.114	0.171	C_3	0.057	0.286	0.114	0.171	0.171	0.114
C_4	0.114	0.086	0.143	0.086	0.086	0.086	C_4	0.057	0.086	0.029	0.086	0.086	0.086
C_5	0.300	0.043	0.257	0.171	0.129	0.086	C_5	0.000	0.257	0.043	0.129	0.171	0.214
C_6	0.357	0.071	0.357	0.286	0.143	0.143	C_6	0.143	0.429	0.143	0.214	0.357	0.357
C_7	0.300	0.100	0.400	0.500	0.500	0.200	C_7	0.300	0.500	0.200	0.100	0.100	0.400
C_8	0.200	0.057	0.171	0.114	0.114	0.200	C_8	0.000	0.143	0.029	0.086	0.086	0.000
C_9	0.200	0.100	0.200	0.200	0.200	0.200	C_9	0.300	0.400	0.300	0.300	0.300	0.300
D^+	1.943	0.529	1.943	1.614	1.386	1.257	D^-	0.929	2.343	0.929	1.257	1.486	1.614

Note. Proposed by the authors.

Table 9. Result of the RC calculation.

Supplier	F_1	F_2	F_3	F_4	F_5	F_6
RC_i	0.323	0.816	0.323	0.438	0.517	0.562
RC_i normalized	0.281	0.849	0.281	0.421	0.528	0.588
Ranking	6th	1st	5th	4th	3rd	2nd

Note. Proposed by the authors.

Table 10. Evaluation of suppliers with respect to the criteria of the 'capabilities' dimension.

C_i	Decision-maker 1						Decision-maker 2					
	F_1	F_2	F_3	F_4	F_5	F_6	F_1	F_2	F_3	F_4	F_5	F_6
C_1	[VL]	[VL]	[VL]	[VL]	[VL]	[VL]	[M,H]	[M,H]	[M,H]	[M,H]	[M,H]	[P]
C_2	[L,M]	[L,M]	[L,M]	[L,M]	[L,M]	[VL]	[L,M]	[P]	[M,H]	[L,M]	[L,M]	[VL,L,M]
C_3	[M,H]	[M,H]	[L,M]	[M,H]	[M,H]	[VL,L]	[M,H]	[P]	[M,H]	[M,H]	[H,VH]	[M,H,VH]
C_4	[L,M]	[M,H]	[H,VH]	[H,VH]	[H,VH]	[M,H]	[L,M]	[H,VH]	[M,H]	[M,H]	[L,M]	[L,M]
C_5	[VL,L]	[H,VH]	[M,H]	[M,H]	[M,H]	[M,H]	[L,M,H]	[L,M,H]	[L,M]	[L,M]	[L,M,H]	[H,VH]
C_6	[M,H]	[M,H]	[M,H]	[H,VH]	[M,H]	[H,VH]	[L,M]	[L,M]	[VL,L]	[L,M]	[L,M]	[L,M]
C_7	[M,H]	[M,H]	[M,H]	[H,VH]	[M,H]	[H,VH]	[M,H]	[M,H]	[L,M]	[M,H]	[M,H]	[H,VH]
C_8	[L,M]	[P]	[M,H]	[M,H]	[M,H]	[M,H]	[L,M]	[H,VH]	[L,M]	[M,H]	[M,H]	[M,H]
C_9	[L,M]	[P]	[M,H]	[M,H]	[M,H]	[M,H]	[L,M]	[M,H]	[L,M]	[M,H]	[M,H]	[M,H]
C_{10}	[L,M]	[M,H]	[L,M]	[VL,L]	[VL,L]	[H,VH]	[M,H]	[M,H]	[VL,L]	[L,M]	[L,M]	[H,VH]
C_{11}	[M,H]	[H,VH]	[M,H]	[M,H]	[M,H]	[M,H]	[H,VH]	[H,VH]	[M,H]	[M,H]	[M,H]	[P]
C_{12}	[P]	[P]	[P]	[P]	[P]	[P]	[P]	[P]	[P]	[P]	[P]	[P]
C_{13}	[L,M]	[H,VH]	[L,M]	[M,H]	[M,H]	[P]	[L,M]	[M,H]	[L,M]	[L,M]	[L,M]	[M,H]
C_{14}	[L,M]	[H,VH]	[L,M]	[L,M]	[L,M]	[P]	[P]	[P]	[H,VH]	[M,H]	[M,H]	[P]
C_{15}	[VH]	[VH]	[VH]	[VH]	[VH]	[VH]	[P]	[P]	[P]	[P]	[P]	[P]
C_{16}	[VL]	[H,VH]	[M,H]	[M,H]	[M,H]	[H,VH]	[VL,L]	[M,H]	[L,M]	[L,M]	[M,H]	[H,VH]
C_{17}	[M,H]	[H,VH]	[M,H]	[M,H]	[M,H]	[H,VH]	[L,M]	[H,VH]	[L,M]	[M,H]	[M,H]	[H,VH]
C_{18}	[M,H]	[H,VH]	[M,H]	[L,M]	[L,M]	[P]	[M,H]	[L,M]	[VL,L]	[L,M]	[L,M]	[H,VH]
C_{19}	[M,H]	[M,H]	[M,H]	[M,H]	[M,H]	[P]	[L,M]	[L,M]	[L,M]	[L,M]	[L,M]	[H,VH]

Note. Proposed by the authors.

Table 11. Standardized RC calculation results for the 'capabilities' dimension.

Supplier	F_1	F_2	F_3	F_4	F_5	F_6
Normalized RC_i	0.285	0.776	0.311	0.406	0.395	0.783
Ranking	6th	2nd	5th	3rd	4th	1st

Note. Proposed by the authors.

Step 3: categorization of suppliers

Step 3 began with the supplier positioning in the segmentation matrix. This positioning was based on the normalized values of RC_i for the dimensions 'willingness to collaborate' and 'capabilities,' as shown in Tables 9 and 11. As defined by Rezaei and Ortt (2013a), the *y*-axis of the matrix corresponds to the 'willingness to collaborate' dimension, and the *x*-axis corresponds to the 'capabilities' dimension. Figure 3 shows the supplier positioning. The last step of the application consisted of the identification of the groups into which each supplier was classified. This identification is important because it provides a basis for the development and implementation of programs and policies for supplier development. As shown in Figure 3, F_1, F_3, and F_4 were positioned in group 1, F_5 was in group 2, and F_2 and F_6 were in group 4. No supplier was positioned in group 3.

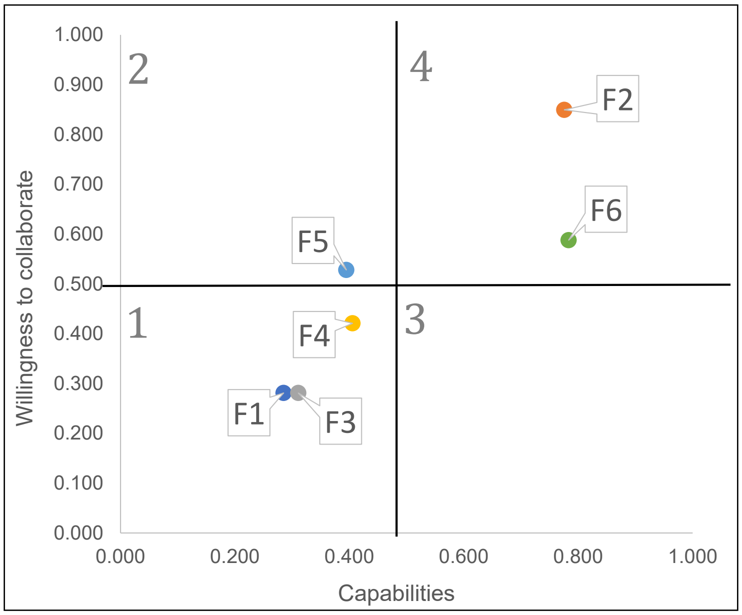


Figure 3. Positioning of suppliers in the segmentation matrix.
Proposed by the authors.

The segmentation matrix serves as a tool in the development of suppliers. Actions may be formulated by the purchasing company managers with the aim of moving suppliers to group 4, which is characterized by suppliers with high degrees of capabilities and willingness to collaborate. These actions should be focused on the criteria in which these suppliers exhibited insufficient performance. For suppliers in group 1, policies and actions focused on increasing their capabilities and willingness to collaborate should be implemented. For suppliers in group 2, actions focused on improving their capacities may help them transfer to group 4. Another issue that must be considered is the development of actions aimed at the maintenance of suppliers who already belong to group 4, considering that there is the possibility of a 'relaxation' of their performance and their regression to another group.

Finally, these results were presented to the decision-makers, who stated that the criteria weights and the supplier classification reflected their preferences. In the 'willingness to collaborate' dimension, the criteria with the largest weights were safety auditorship (C_7) and compliance procedures (C_9), whereas in the 'capabilities' dimension, they were technical knowledge (C_7), safety training (C_{14}) and number of accidents (C_{15}). These criteria directly influenced the segmentation results, as the best-positioned suppliers (F_2 and F_2) achieved high performance in the criteria of largest weight. In contrast F_1 and F_3 had low performance in some of these criteria and did not reach high scores in several others, which led to their classification into group 4. In endorsing the results, the decision-makers affirmed that the criteria weighting reflected the hydroelectric plant's focus on management of occupational safety and social aspects, as accidents in this context can have significant negative impacts in the economic, environmental, and social spheres. These results also reflect the need to meet compliance procedures, as the company is part of a consortium of plants and must satisfy several regulations and demands from various stakeholders.

Sensitivity analysis

In this study, a variation of the HFL-TOPSIS technique proposed by Magalhães (2020) on the basis of the work of Beg and Rashid (2013) was employed. In this approach, it is possible to assign weights to the criteria, which is impossible in the original version proposed by Beg and Rashid (2013). To analyze the consistency of the results obtained using this version of the technique, sensitivity analysis tests were conducted, which revealed the effects of the variations of input parameters on the model output results (Saltelli et al., 2019).

The sensitivity analysis was conducted for three scenarios, whereby parameter variations occurred only in criteria weights so as to preserve supplier scores given by decision-makers. Scenario 1 considers the maximization of the environmental criteria weights; i.e., a higher level of importance was attributed to the weights of these criteria than to the others. This maximization occurred through the assignment of the linguistic judgment 'AB' (absolute) for environmental criteria, whereas the judgment 'M' (medium) was assigned for the other criteria (economic and social). The maximization was simultaneously performed for the 'willingness to collaborate' and 'capabilities' dimensions. In scenario 2, the maximization of the weights occurred in the economic criteria and followed the same logic as scenario 1. In scenario 3, the maximization of the weights of the social criteria was performed. Tables 12 and 13 present the judgments attributed to the weights in scenarios 1 to 3.

Table 12. Judgments of the weights of the criteria of the 'willingness to collaborate' dimension.

Criteria	Scenario 1		Scenario 2		Scenario 3	
	Decision-maker 1	Decision-maker 2	Decision-maker 1	Decision-maker 2	Decision-maker 1	Decision-maker 2
C_1: Effort to reduce material waste	[P]	[P]	[M]	[M]	[M]	[M]
C_2: Ability to work in a team	[M]	[M]	[P]	[P]	[M]	[M]
C_3: Commitment to quality	[M]	[M]	[P]	[P]	[M]	[M]
C_4: Willingness to share information, ideas, technology, and cost savings	[M]	[M]	[P]	[P]	[M]	[M]
C_5: Long-term relationship	[M]	[M]	[P]	[P]	[M]	[M]
C_6: Honesty	[M]	[M]	[M]	[M]	[P]	[P]
C_7: Safety auditorship	[M]	[M]	[M]	[M]	[P]	[P]
C_8: Ease of communication	[M]	[M]	[M]	[M]	[P]	[P]
C_9: Compliance procedures	[M]	[M]	[M]	[M]	[P]	[P]

Note. Proposed by the authors.

Table 13. Judgment of the weights of the criteria of the 'capabilities' dimension.

Criteria	Scenario 1		Scenario 2		Scenario 3	
	Decision-maker 1	Decision-maker 2	Decision-maker 1	Decision-maker 2	Decision-maker 1	Decision-maker 2
C_1: Environmental certifications	[P]	[P]	[M]	[M]	[M]	[M]
C_2: Proper waste disposal	[P]	[P]	[M]	[M]	[M]	[M]
C_3: Disposal of hazardous materials	[P]	[P]	[M]	[M]	[M]	[M]
C_4: On-time shipment	[M]	[M]	[P]	[P]	[M]	[M]
C_5: Technological capability	[M]	[M]	[P]	[P]	[M]	[M]
C_6: Quick problem solving	[M]	[M]	[P]	[P]	[M]	[M]
C_7: Technical knowledge	[M]	[M]	[P]	[P]	[M]	[M]
C_8: Productivity and efficiency	[M]	[M]	[P]	[P]	[M]	[M]
C_9: Quality	[M]	[M]	[P]	[P]	[M]	[M]
C_{10}: Average training time per employee	[M]	[M]	[M]	[M]	[P]	[P]
C_{11}: Employees' healthcare	[M]	[M]	[M]	[M]	[P]	[P]
C_{12}: Child labor	[M]	[M]	[M]	[M]	[P]	[P]
C_{13}: Work conditions	[M]	[M]	[M]	[M]	[P]	[P]
C_{14}: Safety training	[M]	[M]	[M]	[M]	[P]	[P]
C_{15}: Number of accidents	[M]	[M]	[M]	[M]	[P]	[P]
C_{16}: Employee satisfaction	[M]	[M]	[M]	[M]	[P]	[P]
C_{17}: Company reputation	[M]	[M]	[M]	[M]	[P]	[P]
C_{18}: Technical structure	[M]	[M]	[P]	[P]	[M]	[M]
C_{19}: Financial situation	[M]	[M]	[P]	[P]	[M]	[M]

Note. Proposed by the authors.

After the scenarios were defined, the calculation sequence presented in steps 1 and 2 of the model was applied again, and the linguistic judgments concerning the suppliers' evaluation were kept unchanged (Tables 6 and 10). Table 14 presents the results of the tests, highlighting the normalized values of RC_i for the two dimensions of segmentation in the three scenarios.

Table 14. Normalized RC values for the three scenarios tested.

F_i	Proposed model		Scenario 1		Scenario 2		Scenario 3	
	Willingness	Capabilities	Willingness	Capabilities	Willingness	Capabilities	Willingness	Capabilities
F_1	0.242	0.284	0.250	0.420	0.218	0.233	0.309	0.348
F_2	0.821	0.793	0.798	0.874	0.793	0.734	0.834	0.715
F_3	0.277	0.354	0.250	0.420	0.255	0.376	0.309	0.326
F_4	0.449	0.363	0.634	0.420	0.534	0.409	0.309	0.348
F_5	0.651	0.388	0.634	0.500	0.631	0.409	0.656	0.370
F_6	0.539	0.769	0.432	0.275	0.583	0.806	0.540	0.832

Note. Proposed by the authors.

The groups into which the suppliers were classified in the application case and in the three sensitivity analysis scenarios are presented in Table 15. The values in bold indicate the suppliers that changed groups in relation to the application case. F_1, F_2, F_3 and F_5 had their scores changed in both segmentation dimensions in the three scenarios, but their grouping remained the same, indicating the stability of the model results.

Table 15. Grouping of suppliers for the three scenarios.

Supplier	Application case	Scenario 1	Scenario 2	Scenario 3
F_1	1	1	1	1
F_2	4	4	4	4
F_3	1	1	1	1
F_4	1	**2**	**2**	1
F_5	2	2	2	2
F_6	4	**1**	4	4

Note. Proposed by the authors.

With the exception of scenario 3, which prioritizes social criteria, one can observe variations in the groupings of F_4 and F_6. The variations in the environmental and economic criteria weights impacted with greater intensity the supplier categorization. Although the decision-makers chose a relatively small amount of environmental criteria, the most significant variation was evidenced in scenario 1, where F_6 moved from group 4 to group 1. Although the use of a smaller quantity of environmental criteria in the application case may imply a less thorough evaluation of the suppliers' environmental performance, the results reinforce the significant impact of these environmental criteria on the grouping of suppliers. They also indicate the sensitivity of the model to variations in the values of the weights and demonstrate the importance of considering them in the supplier segmentation, as they can directly affect the grouping results.

In addition to the sensitivity analysis, for comparison, the model was applied while considering only the economic criteria and maintaining the same input scores. This caused changes in the scores of suppliers (RC_i) and changes in categorization, as occurred with F_4, which was moved from group 1 to group 4. These results indicate that the use of environmental and social criteria can impact the categorization, so that suppliers with better socio-environmental performance end up being better positioned in the segmentation matrix. Thus, the buying company starts to strengthen its relationships with suppliers that satisfy the economic, environmental, and social criteria in a balanced manner, rather than focusing on those with high economic performance and low environmental and social performance (for example, F_4).

CONCLUSION

A HFL-TOPSIS model was proposed for supplier segmentation based on the TBL criteria to support group decisions in scenarios of uncertainty and hesitation. In a pilot application conducted in a hydroelectric power plant, the performance of six suppliers was analyzed, and the suppliers were classified according to 28 criteria related to TBL. The classification results were endorsed by the decision-makers involved. Sensitivity analysis tests reinforced the consistency of the obtained results. The model can subsidize the preparation of supplier development programs focused on the sustainability of operations. It can also be applied in situations where the main objective is not to improve the sustainability of the supply chain. In such cases, it is possible to resort to the literature in search of criteria related to more specific objectives for the context in question.

Compared with the previous models presented in Table 1, the proposed model has the advantage of using economic, environmental, and social criteria in the segmentation process and supporting decisions under hesitation. It also has advantages over Torres-Ruiz and Ravindran (2018) model, which is the only previous model for supplier segmentation that considers economic, environmental, and social criteria. In contrast to the model of Torres-Ruiz and Ravindran (2018), the proposed model allows the assignment of terms and linguistic expressions, has no limitation on the number of alternatives or criteria, and requires a smaller amount of judgments by not requiring the performance of paired comparisons between the criteria and alternatives. Therefore, some of the main limitations existing in the AHP technique, which was applied by Torres-Ruiz and Ravindran (2018) and several other researchers (Akman, 2015; Bianchini et al., 2019; Che, 2011; Park et al., 2010; Rezaei & Ortt, 2013a; Santos et al., 2017; Segura & Maroto, 2017), can be circumvented by using the proposed model. This is also valid for models based on the fuzzy-AHP method (Haghighi, Morad, & Salahi, 2014; Lo & Sudjatmika, 2015).

As a suggestion for future research, the proposed model can be replicated by companies in different economic sectors, as this would allow a comparison of the importance that decision-makers attribute to certain criteria between different industries. The set and quantity of criteria selected depend on the needs of the buying company. Although the use of economic and social criteria predominates in the presented case, given the needs of the company in question, future applications may consider environmental, social, and economic criteria in a balanced manner. Another suggestion for future research is to conduct comparative studies between existing supplier segmentation models in the literature. Furthermore, the HFL-TOPSIS technique can be tested on other problems in the area of sustainable supply chain management, such as supplier selection using TBL criteria, evaluation of supplier development programs, and sustainable supply chain performance measurement.

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Funding

The author reported that there is no financial support for the research in this article.

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The RAC maintains the practice of submitting all documents approved for publication to the plagiarism check, using specific tools, e.g.: iThenticate.

Authors' Contributions

1st author: conceptualization (lead); formal analysis (lead); investigation (lead); methodology (lead); validation (lead); visualization (lead); writing – original draft (lead).

2nd author: conceptualization (equal); methodology (equal); project administration (lead); supervision (equal); validation (lead); writing – original draft (supporting).

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Conflict of Interests

The authors have stated that there is no conflict of interest.

Peer Review Method

This content was evaluated using the double-blind peer review process. The disclosure of the reviewers' information on the first page, as well as the Peer Review Report, is made only after concluding the evaluation process, and with the voluntary consent of the respective reviewers and authors.

Data Availability

The authors claim that all data used in the research have been made publicly available through the Harvard Dataverse platform and can be accessed at:

Borges, William Viana; Lima Junior, Francisco Rodrigues; Peinado, Jurandir; Carpinetti, Luiz Cesar Ribeiro, 2021, "Replication Data for: "A Hesitant Fuzzy Linguistic TOPSIS model to support Supplier Segmentation" published by RAC - Revista de Administração Contemporânea", Harvard Dataverse, V1. https://doi.org/10.7910/DVN/B33ARK

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