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An Approach for Sustainable Supplier Segmentation Using Adaptive Network-Based Fuzzy Inference Systems

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Abstract

Due to the globalization of supply chains and the resulting increase in the quantity and diversity of suppliers, the segmentation of suppliers has become fundamental to improving relationship management and supplier performance. Moreover, given the need to incorporate sustainability into supply chain management, criteria based on economic, environmental, and social performance have been adopted for evaluating suppliers. However, few studies present sustainable supplier segmentation models in the literature, and none of them make it possible to predict individual supplier performance for each TBL dimension in a non-compensatory manner. Moreover, none of them permits the use of historical performance data to adapt the model to the usage environment. Given this, this study aims to propose a decision-making model for sustainable supplier segmentation using an adaptive network-based fuzzy inference system (ANFIS). Our approach combines three ANFIS computational models in a tridimensional quadratic matrix, based on diverse criteria associated with the triple bottom line (TBL) dimensions. A pilot application of this model in a sugarcane mill was performed. We implemented 108 candidate topologies using the Neuro-Fuzzy Designer of the MATLAB® software (R2014a). The cross-validation method was applied to select the best topologies. The accuracy of the selected topologies was confirmed using statistical tests. The proposed model can be adopted for supplier segmentation processes in companies that wish to monitor and/or improve the sustainability performance of their suppliers. This study may also be helpful to researchers in developing computational solutions for segmenting suppliers, mainly regarding ANFIS modeling and providing appropriate topological parameters to obtain accurate results.

Keywords: sustainable supplier segmentation; ANFIS; supplier categorization; sustainable supply chain management

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1. Introduction

Over the past few decades, more rigid environmental legislation and stakeholder pressure for greater profitability have made companies promote improvements in the sustainability of their operations [1]. According to [2], the implementation of sustainability "requires organizations to extend their focus beyond the traditional economic objectives to embrace a triple-bottom-line (TBL) approach that requires them to simultaneously meet or make trade-offs between economic, environmental, and social goals". These authors also point out that it is difficult to achieve sustainability in a company's operations without the support of its suppliers. Within this context, supplier relationship management has become essential to optimizing the supplier base and making the supply chain performance more sustainable [3].

With the advent of global supply chains, the quantity and diversity of suppliers available in the market have increased drastically, which has made managing supplier relationships more complex [4,5]. Given this, the segmentation of suppliers presents itself as an effective way to manage the supplier base, because grouping suppliers with characteristics in common limits the number of relationship strategies necessary to manage the supplier base and promote more effective management [2]. Supplier segmentation can help managers allocate specific resources to certain relationships to create development strategies appropriate for the supplier's profile [6].

Various studies in the literature propose using quantitative models to support supplier segmentation [3,6]. In recent years, this subject has received more interest from researchers, given the capacity of these models to support decision-making in an automated manner [5]. In general, classifying suppliers is based on criteria associated with the dimensions of the supplier's performance [1,7]. Even though there are dozens of decision-making models to support supplier segmentation, most of them classify suppliers only based on economic aspects [6].

As shown in Table 1, based on the studies in a systematic review of this subject [3,8,9] and bibliographic research realized for this study, we have found just twelve studies which propose quantitative models to support sustainable supplier segmentation [6,10–20]. In other words, just twelve models considered economic, environmental, and social criteria in the supplier segmentation process.

Table 1. This Study's Contributions in Comparison to Previous Supplier Segmentation Models.

	[6]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Our Study
Does it offer support for sustainable supplier segmentation?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Does it have a supervised learning process?	No	No	No	No	No	No	No	No	No	No	No	No	Yes
Is segmentation based on economic, environmental, and social dimensions?	No	No	No	Yes	Yes	No	No	No	Yes	No	Yes	No	Yes
Is there compensation among the TBL dimensions or criteria?	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Does it have the capacity to model nonlinear relationships between inputs and outputs?	No	No	No	No	No	No	No	No	No	No	No	No	Yes
Does the model include decision rules?	No	No	No	No	No	No	No	No	No	No	No	No	Yes

Based on the analysis of the studies detailed in Table 1 [6,10–20], the following research gaps were identified, which this study aims to address:

i. Lack of supervised learning capabilities using historical data: Despite the diversity of techniques explored for supplier segmentation, none of the existing models incorporate a supervised learning procedure based on historical supplier performance [3,6]. This limitation hinders the use of data from periodic supplier assessments to refine cause-and-effect relationships between input and output variables. While current models rely heavily on Multi-criteria Decision Making (MCDM) methods, they remain static and cannot be tuned or updated through accumulated historical evidence.

ii. Inability to capture nonlinear relationships among segmentation criteria: As MCDM methods typically produce a global ranking for each alternative based on weighted combinations of inputs, they are limited to linear aggregation and fail to represent nonlinear cause-and-effect dynamics. However, in supplier evaluation, many relationships are inherently nonlinear (e.g., $x = y/z$ and $x = z \cdot y^2$),which makes such methods inadequate for contexts where complex interactions exist among sustainability indicators [21].

iii. Absence of an inference rule base to support decision-making: Current sustainable supplier segmentation models also lack a structured rule base to guide the decision process. Without such a mechanism, decision-making becomes less transparent, harder to justify, and more dependent on expert judgment, which can introduce subjectivity and inconsistency.

Adaptive Network-based Fuzzy Inference Systems (ANFISs) are hybrid models that combine the learning ability of artificial neural networks with the interpretability of fuzzy inference systems. They were chosen in this study as a means to address the research gaps identified. Several advantages can justify the choice. First, ANFIS can adapt to the usage environment through supervised learning, providing flexibility to accommodate diverse decision-making contexts. Second, they are particularly suitable for decision-making under uncertainty, as the fuzzy component allows the treatment of imprecise, subjective, or incomplete information that typically characterizes sustainability assessments. Third, after being trained with supplier performance data, ANFIS models can predict global performance values across each TBL dimension, supporting more comprehensive evaluations [21,22].

In this context, this article aims to propose a decision-making model for sustainable supplier segmentation based on ANFISs. This study advances the supplier segmentation literature by introducing a model based on supervised learning and nonlinear modeling, which leverages historical performance data to capture complex interactions among criteria automatically. In addition, it enhances transparency through interpretable decision rules and provides practical guidelines for defining appropriate ANFIS topological parameters, ensuring both accuracy and computational efficiency.

The rest of the article is organized in the following manner. Section 2 presents theoretical references to sustainable supplier segmentation and ANFISs. Section 3 will detail the proposed model, while Section 4 will present the results of its application. Section 5 will discuss the results of the statistical tests used to validate the model. Finally, this study's conclusions and limitations are presented in Section 6.

2. Theoretical Framework

2.1. Sustainable Supplier Segmentation

Day et al. [8] conceptualized 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 to obtain exchange value". The inclusion of environmental and social criteria makes the supplier segmentation process more effective [3,6], given that the economic, social, and environmental commitment to stakeholders has required the adoption of practices to improve the sustainable performance of suppliers [1]. Social and environmental performance improvements benefit organizations because they fulfill the needs of the stakeholders and indirectly carry out economic improvements [11]. Thus, supplier segmentation based on the TBL criteria has become a crucial practice enabling companies to improve their sustainability of supply chains [6].

A suitable decision-making method must be applied to classify suppliers in terms of each performance dimension in the supplier segmentation process [23,24]. The literature presents several studies that propose supplier segmentation models based on decision-making methods to categorize suppliers into segmentation matrices. Table 2 lists some studies that propose decision-making models for supplier segmentation. This table only presents studies published since 2013 to update the state of the art concerning this subject, and it includes some models that have not appeared in previous systematic reviews of the literature [3,8,9]. These studies were collected based on the Science Direct, Springer, Scopus, Emerald Insight, IEEE Xplore®, Taylor & Francis, and Wiley databases, per the procedures presented by [9]. Table 2 describes the techniques and performance dimensions considered in the supplier segmentation matrices. In this table, the symbol "X" denotes the type of supply chain management strategy considered in each study, which is directly related to the segmentation dimensions and supplier evaluation criteria.

Table 2. Previous Decision Models to Support Supplier Segmentation.

Proposed by	Decision-Making Techniques	Segmentation Dimensions	Supply Chain Management Strategy				
			Traditional	Green	Agile	Resilient	Sustainable
[4]	Fuzzy c-means and VIKOR	Does not adopt segmentation dimensions		X			
[16]	TOPSIS and Fuzzy DEMATEL	Does not adopt segmentation dimensions					X
[25]	Fuzzy inference	Supplier attractiveness and strength of the relationship	X				
[20]	DEA and AHP	Does not adopt segmentation dimensions				X	X
[2]	Rough Sets, VIKOR, and fuzzy c-means	Supplier capabilities and willingness		X			
[26]	AHP	Profit impact and supply risk	X				
[6]	Hesitant Fuzzy Linguistic-TOPSIS	Supplier capabilities and willingness					X
[27]	PROMETHEE	Supplier capabilities and willingness	X				
[12]	ANP, PROMETHEE, and cluster analysis	Economic, environmental, and social					
[28]	VIKORSORT	Does not adopt segmentation dimensions		X			
[29]	Fuzzy logic	Supplier capabilities and willingness		X			
[30]	Fuzzy-AHP and Fuzzy c-means	Supplier capabilities and willingness	X				
[31]	Fuzzy c-means and Fuzzy formal concept analysis	Supplier investment decisions and supplier collaboration decisions		X			
[32]	DEA	Does not adopt segmentation dimensions	X				
[33]	K-means	Does not adopt segmentation dimensions	X				
[17]	Bayesian best-worst method and Canopy-K-Means clustering algorithm	Economic, environmental, and social					X
[34]	Fuzzy-TOPSIS	Cost and delivery performance	X				
[35]	Fuzzy-AHP	Supplier capabilities and willingness	X				
[36]	K-means	Does not adopt segmentation dimensions	X				
[13]	Fuzzy-AHP and Fuzzy equivalence relation	Economic, environmental, social, and risk					X
[37]	Fuzzy-TOPSIS	Profit impact and supply risk	X				
[18]	Stochastic multi-objective programming	Profit, capability, and willingness					X
[38]	BWM and K-means	The model does not rely on predefined segmentation dimensions				X	
[39]	Fuzzy inference	Potential for partnership and delivery performance	X				

Table 2. *Cont.*

Proposed by	Decision-Making Techniques	Segmentation Dimensions	Supply Chain Management Strategy				
			Traditional	Green	Agile	Resilient	Sustainable
[40]	Grey DEMATEL and Grey Simple Additive Weighting technique	Resiliency enhancer and resiliency reducer				X	
[19]	BWM and Grey Simple Additive Weighting	Economic, environmental, and social					X
[14]	BWM and K-means	Profit impact and supply risk					X
[41]	Fuzzy inference	Agility capability and business excellence			X		
[42]	DEA	Diversity, efficiency, and cross efficiency	X				
[7]	BWM	Supplier capabilities and supplier willingness	X				
[43]	Fuzzy preference relation-based AHP	Supplier capabilities and supplier willingness	X				
[44]	AHP	Supplier capabilities and supplier willingness	X				
[45]	ELECTRE TRI-rC	Supplier capabilities and supplier willingness		X			
[46]	BWM	Supplier capabilities and supplier willingness	X				
[11]	Procedure based on the arithmetic mean	Profit impact and supply risk					X
[47]	AHP and Fuzzy 2-tuple	Supplier capabilities and supplier willingness		X			
[48]	AHP, PROMETHEE, and MAUT	Critical performance and strategic performance	X				
[15]	BWM and PROMETHEE	Critical performance and strategic performance of suppliers					X
[10]	AHP	Supplier risks, country risks, and risk management practice					X

As shown in Table 2, most of the studies have considered a traditional supply chain management strategy that focuses more on economic performance. We found just twelve models oriented towards sustainable supplier segmentation [6,10–20]. Except the studies by [12,19], all sustainable supplier segmentation models in the literature adopted a compensatory approach. This means that high performance in one dimension partially offsets low performance in another. However, compensatory approaches do not allow for the identification of suppliers that exhibit low performance in specific dimensions, thus hindering the attainment of a balanced performance level across all three dimensions of the TBL. Additionally, compensatory models cannot identify the need for direct actions to improve economic, environmental, and/or social aspects.

Another limitation of the previous supplier segmentation models is their difficulty adapting to the specific usage environment and their challenge in modeling nonlinear relationships among performance measures. Despite the variety of techniques in Table 2, none can tune the model's parameters to the usage environment based on historical performance data.

Furthermore, the only models based on decision rules are those using fuzzy inference systems [25,39,41]. However, these approaches are not specifically designed for sustainable supplier segmentation. Nevertheless, the manual parameterization of dozens or hundreds of rules required by these inference systems makes the modeling phase exceedingly time-consuming for DMs. It may lead to inconsistent results due to errors in rule settings. Thus, since the previous models do not use any supervised learning algorithm, they are not able to computationally adjust cause and effect relationships between the input and output variables. Developing ANFIS models to support the supplier segmentation process can overcome these limitations.

2.2. Adaptive Neuro-Fuzzy Inference Systems

In the literature, various types of techniques combine fuzzy logic with artificial neural networks, generally known as neuro-fuzzy systems [21]. The most popular of these was proposed by Jang [49], and it is called an Adaptive Neuro-Fuzzy Inference System or ANFIS. As discussed in Section 2.1, applying fuzzy inference systems requires a considerable effort to define inference rules and membership functions [3]. Neural networks, on the other hand, when used in an isolated manner, do not promote transparency in their calculations and are not appropriate for making decisions under conditions of uncertainty. These limitations can be overcome by combining these two techniques, which generates a model with superior predictive capacity and greater transparency regarding its results [22,50]. The ANFIS structure allows the model to adaptively learn nonlinear relationships and interactions among the input variables, capturing complex patterns that may not be representable with a simple mathematical formula [21].

Figure 1 presents the topology of the ANFIS model with three input variables and one output variable. This system possesses five layers; within each one, some nodes perform the same functions. Circles represent the fixed nodes, while squares indicate the adaptive nodes. The adaptive nodes are adjusted during system training through modifiable parameters. The functioning of each layer is described below [21,22]:

(a) Layer 1: In this layer, the input values (x and y) in crisp format are converted into fuzzy set equivalents. Their function can be given as:

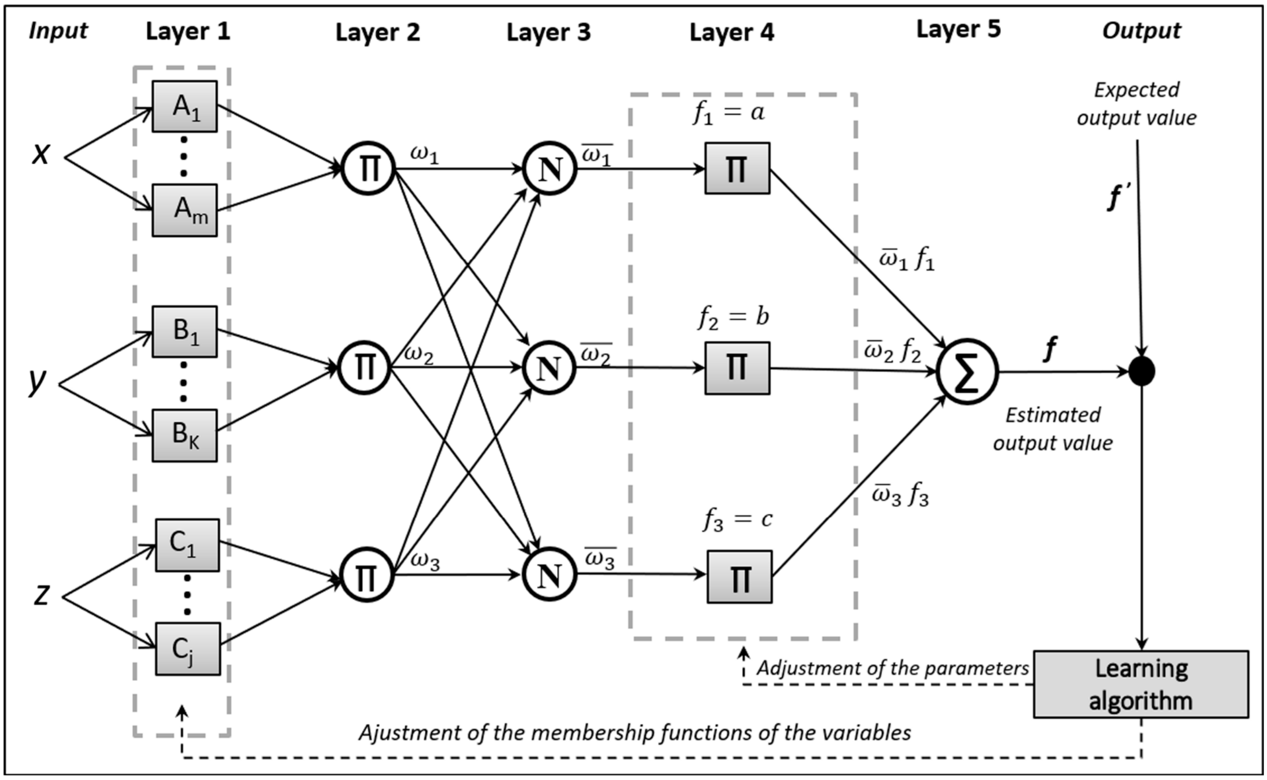

Figure 1. Structure of the ANFIS Model with Three Input Variables.

$$O_i^1 = \mu_{Ai}(x) \tag{1}$$

where x is the input of the node and A_i is the linguistic variable associated with the node function. The output O_i^1 is the degree to which value x belongs to the fuzzy set defined by the variable A_i. The membership function is defined for an interval [0, 1], in which 1 signifies that x totally belongs to the set and 0 means that x does not belong to the set.

(b) Layer 2: This layer combines all of the previous layer's nodes to establish the logical relationships among the activated membership functions. This layer represents the antecedent part of the decision-making rules, which realizes operations of "AND" or "OR". The equation that represents the realized operation for this combination layer is given by:

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(x),\ \text{for}\ i = 1, 2, 3 \ldots \text{n} \tag{2}$$

The output of this layer is made up of the relationships among all of the linguistic input terms, resulting in a membership degree w_i, which determines the weight of each activated rule;

(c) Layer 3: This layer normalizes the weights of the activated rules. Equation (3) describes the procedure.

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2 + w_3 + \cdots + w_n},\ \text{for}\ i = 1, 2, 3 \ldots \text{n} \tag{3}$$

(d) Layer 4: This is the layer of the adaptive nodes that represents the rule consequents. These consequents generate outputs for each activated rule according to Equation (4). A linear function or a constant function can produce the consequent value. The output value of this layer is calculated by the simple product of the consequent of each rule (f_i) and the weight of the rule activated in the third layer.

$$O_i^4 = \overline{w}_i f_i,\ \text{for}\ i = 1, 2, 3 \ldots \text{n} \tag{4}$$

(e) Layer 5: This layer is composed of a fixed node that calculates a weighted sum of the previous layer's outputs, as represented by Equation (5).

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

To conduct the learning process for an ANFIS, one needs to have sample values for the input and output variables. These samples should be divided into two groups: 60 to 90% of the samples for the training set, and 10 to 40% for the validation set. The first set should be used to adjust the adaptive parameters. The second set should be applied to verify the model's accuracy [22,50].

One of the supervised learning algorithms most often used to train ANFIS models is the hybrid algorithm proposed by [49]. This algorithm applies the least squares method to adjust adaptive parameters for the inputs, and the gradient descent method to adjust the consequents of the rules to minimize the errors between the values produced by the model and the output value of each training sample. The number of times that the model processes the training samples is called the epoch number, which serves as a stop criterion [21]. After the training has been completed, the validation of the model can be performed based on the MSE (Mean Squared Error) or RMSE (Root Mean Squared Error) obtained using the validation set.

The type of the membership function, the number of membership functions, and the types of consequent and logical operators are the parameters that directly affect the accuracy of ANFIS models. This is why it is necessary to perform various computational tests to select the best topology for each model. The cross-validation technique can be adopted to support the choice of the best topologies. This technique is based on the realization of several tests by varying the model's topological parameters [21,50,51].

ANFIS continues to attract research interest in the field of intelligent decision-making. For instance, ref. [52] proposed an advanced neuro-fuzzy framework that handles high-dimensional datasets with more than 7000 features, integrating feature selection and rule extraction in a single architecture. This study demonstrates the ongoing evolution of neuro-fuzzy systems to overcome traditional scalability limitations.

3. The Proposed Model for Sustainable Supplier Segmentation

Our theoretical model, designed to support sustainable supplier segmentation, is presented in Figure 2. This model is divided into three steps and was developed based on [21,53,54]. It involves using three ANFIS computational models, one for each TBL dimension. Besides permitting the grouping of suppliers based on similar performance levels, the proposed model offers a base for elaborating action plans that seek to develop suppliers in economic, environmental, and social terms.

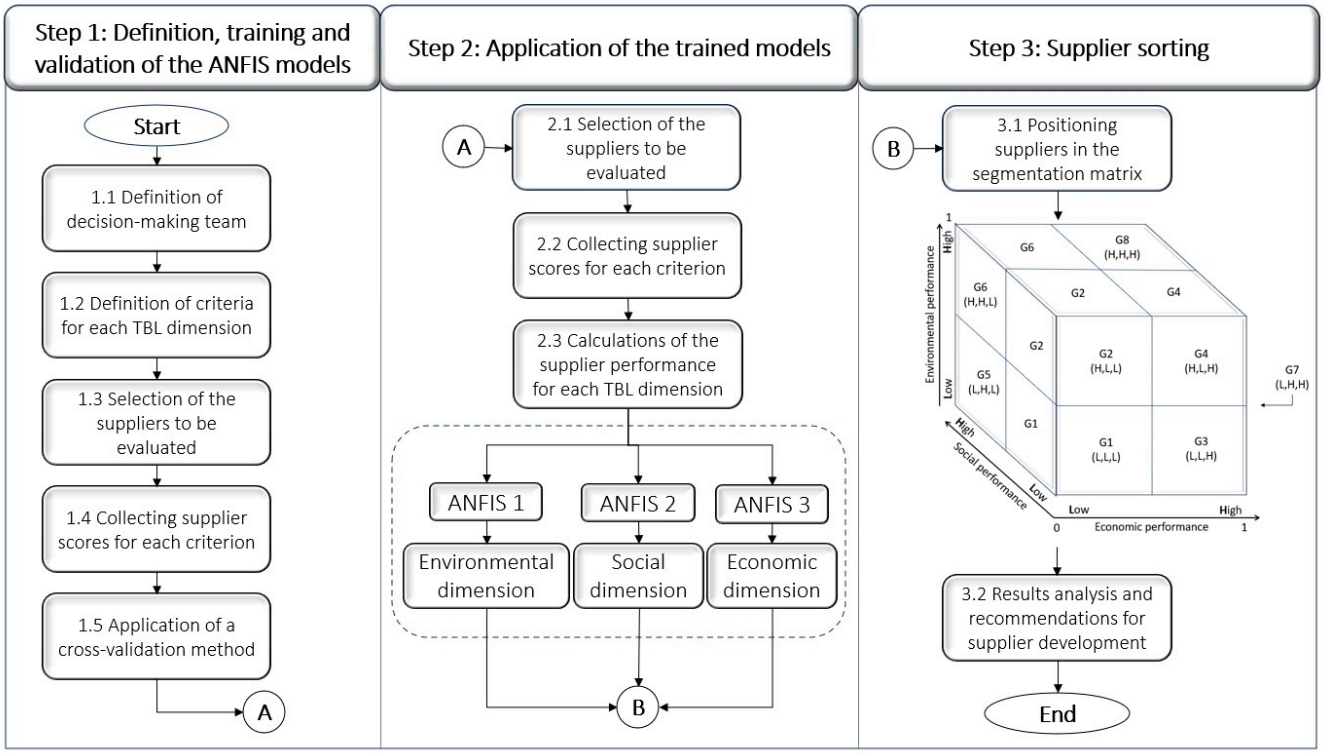

Figure 2. Proposed Model for Sustainable Supplier Segmentation.

In Figure 2, A and B are connectors that indicate the flow between the stages of the model; they do not represent specific activities. Stage 1 begins with assembling a decision-making team (Step 1.1). This team should comprise professionals from the sales, quality management, socio-environmental management, and/or supplier development areas and other employees linked to supply chain management. The DMs play a central role in defining the supplier evaluation criteria and interpreting the model results. In Step 1.2, the team will select the most important criteria to be analyzed for each TBL dimension, and the selected criteria should be aligned with the company's performance targets. Table A1 (see Appendix A) presents some examples of possible criteria for each dimension. This list was compiled based on previous studies on sustainable supplier segmentation [6,10–20].

Step 1.3 involves defining the suppliers that the buying company will evaluate. The focus of this evaluation is on the qualified suppliers who have already been hired by the buying company. In Step 1.4, a score is assigned individually for the performance of each supplier in relation to each criterion chosen in Step 1.2. These scores can be defined based on historical data from the buying company through performance indicators, ERP (Enterprise Resource Planning) systems, or BI (Business Intelligence) systems, among other management support systems. In the absence of historical data, or when it is insufficient, it is possible to form a committee of DMs in supply chain-related areas to collect the opinions of these specialists in judging these suppliers in terms of each criterion.

In Step 1.5, the cross-validation technique must be applied to build and tune the ANFIS models. Figure 3 presents the steps of applying the proposed cross-validation technique explicitly designed for ANFISs. This procedure aims to identify the most accurate and robust model topology by systematically evaluating various parameter configurations based on their predictive performance. Step i of Figure 3 begins with the organization of the available dataset, which involves partitioning the complete set of samples into two subsets: a training set and a validation set. The training set is used to adjust the internal parameters of the ANFIS models during the learning phase. In contrast, the validation set serves as an independent means to evaluate the model's generalization capability.

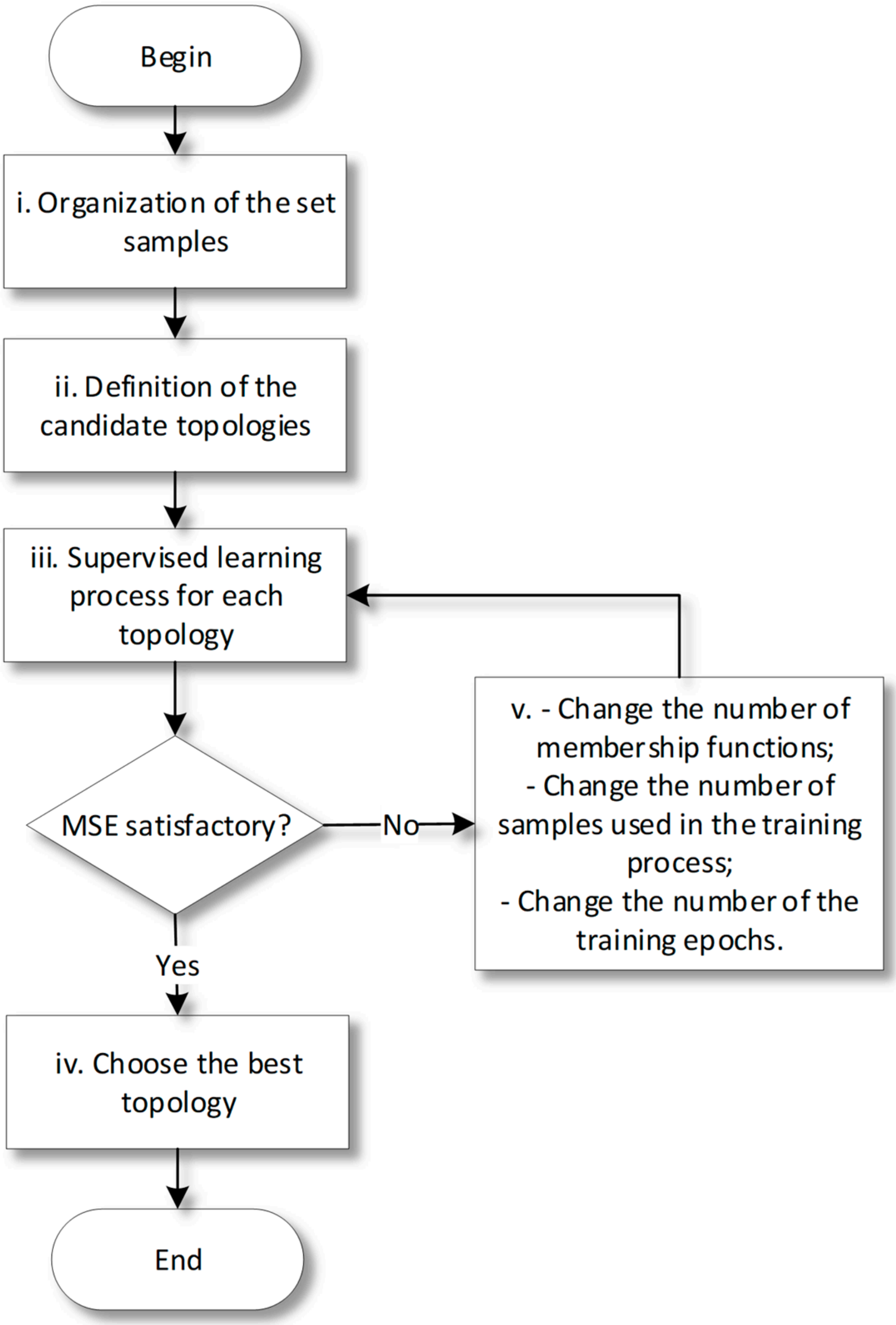

Figure 3. Cross-Validation Steps for ANFIS.

Next, in Step ii, a series of candidate topologies is defined. Each topology represents a unique configuration of internal ANFIS parameters. The range of values to be tested for each parameter should be established based on prior literature or determined empirically through preliminary computational experiments. Once the candidate topologies have been established, a supervised learning process is applied to each model configuration (Step iii). This study utilized the Neuro-Fuzzy Designer tool from MATLAB® (MathWorks, Natick, MA, USA) to conduct training and validation phases. The training samples were used to iteratively tune the internal parameters of each topology using a hybrid learning algorithms that combine least-squares estimation and backpropagation.

After the training phase, each model's performance is quantitatively assessed using the MSE (or RMSE) on the validation dataset. These metrics are computed by comparing the predicted outputs of the ANFIS model against the actual target values in the validation set. This evaluation step is critical for determining the generalization capability of each candidate model. A decision point is reached: if the MSE obtained is considered satisfactory, the process proceeds to Step iv, where the best topology is selected. If none of the tested topologies meet the desired performance threshold, the process moves to Step v, where a refinement strategy is implemented. This involves modifying one or more of the following aspects:

- Changing the number of membership functions, which affects the granularity of the fuzzy inference process;
- Increasing the number of training samples to enhance the model's learning capacity.
- Adjusting the number of training epochs will allow the model to have more iterations to converge.

After these modifications are made, the process loops back to Step ii, where new candidate topologies are generated and the cross-validation cycle is repeated until a satisfactory model is obtained.

Stage 2 focuses on applying the ANFIS models to the supplier segmentation process. Step 2.1 consists of defining the suppliers to be segmented based on the TBL dimensions, while Step 2.2 focuses on obtaining the scores of these suppliers for each criterion. Since collecting data from all suppliers can be difficult and time-consuming, it is recommended only to include suppliers that are important to the company, such as the suppliers of strategic, leverage, or bottleneck items. In Step 2.3, the supplier scores for each criterion should be input into the ANFISs, which has been trained in the previous stage. Then, each ANFIS model will estimate the global performance of each supplier in a specific dimension. While the ANFIS 1 model will calculate the overall performance values regarding the environmental dimension, the ANFIS 2 and 3 models will estimate the overall performance regarding the social and economic dimensions, respectively.

In Stage 3 of the proposed model, each supplier should be classified in one of eight possible groups defined in Figure 4. This classification helps buyers define appropriate actions to manage their supplier base and improve the performance of the suppliers. Each dimension of the segmentation matrix represents a TBL dimension. Each group is represented as $G_i(f(Y_1), f(Y_2), f(Y_3))$, with ($i$ = 0, 1, . . ., 8). The values of $f(Y_m)$ (m = 1, . . ., 3) indicate the supplier classification results for each dimension. If $f(Y_m) \geq t_m$, then $f(Y_m)$ = "High (H)". Otherwise, $f(Y_m)$ = "Low (L)". The values of t_m should be defined by the team of DMs. A universal mathematical formula cannot determine these thresholds, as it is inherently a subjective choice. For example, a given level of environmental performance may be considered high by one organization but low by another, depending on internal standards, strategic objectives, and external pressures. In our approach, an initial symmetric partitioning is adopted, with a threshold set at 0.5, which provides a neutral starting point for classification. This threshold can be gradually adjusted over time based on practical experience, organizational priorities, and evolving sustainability goals.

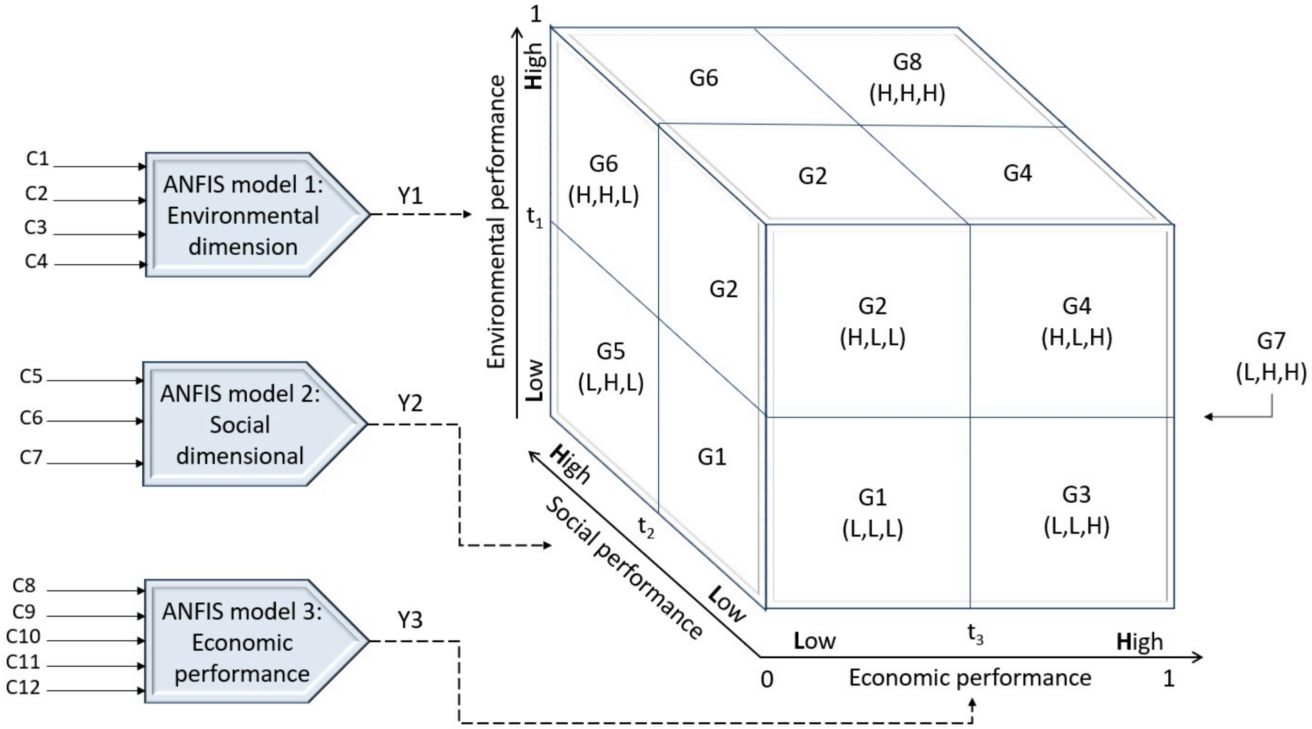

Figure 4. The Proposed Sustainable Supplier Segmentation Matrix.

In the matrix shown in Figure 4, suppliers with similar performance for the three TBL dimensions must be classified in the same group. The features of the suppliers classified in each one of the groups shown in Figure 4 are described as follows [53]:

(a) G1 (L, L, L)—This group consists of the suppliers with the worst performance evaluations, or those with poor economic, environmental, and social performance. The suppliers in this group should be substituted if possible [53]. Otherwise, supplier development programs should be implemented to achieve improved supplier performance in the three dimensions of the TBL.

(b) G2 (H, L, L)—This group consists of suppliers that have achieved good environmental performance and poor economic and social performance. The suppliers in this segment generally focus on efficient use of natural resources and controlling and preventing pollution.

(c) G3 (L, L, H)—This group consists of suppliers with good economic performance and poor social and environmental performance. They operate their supply chains with a focus on profits and are not concerned with environmental and social issues.

(d) G4 (H, L, H)—This group comprises suppliers with satisfactory economic and environmental performance, but poor social performance. They generally reduce costs through their efficient use of energy and natural resources.

(e) G5 (L, H, L)—This group consists of suppliers with good social performance and poor economic and environmental performance. They are focused on social justice. They emphasize diversity in their labor, human rights, a reduction in inequality, and the quality of life of their employees.

(f) G6 (H, H, L)—This group consists of suppliers with poor economic performance and good social and environmental performance. They emphasize using just a portion of natural resources in domestic and international spheres.

(g) G7 (L, H, H)—This group comprises suppliers with good social and economic performance and poor environmental performance. These suppliers seek to reduce costs, considering the social needs of society. They have ethical standards and ensure just business practices that protect the human rights of their employees.

(h) G8 (H, G, G)—This group consists of sustainable suppliers with good social, economic, and environmental performance. They focus on improving their products and the quality of life of people, prioritizing environmental activities, and maximizing renewable natural resources at the least possible cost.

The results of supplier segmentation using the proposed approach make it possible for managers to formulate action plans to move their suppliers toward Group 8 (sustainable suppliers). These plans can be based on specific strategies for each supplier group to improve supplier management effectiveness and fill the identified performance gaps. Table 3 presents some suggested supplier development strategies, separated by TBL dimension.

Table 3. Supplier Development Strategies.

Performance Dimension	Supplier Development Strategies	Supplier Groups
Environmental	- Build top management commitment/support in the supplier organization for green supply practices [54]. - Consult suppliers about green production [55]. - Give rewards to suppliers for their environmental performance [46]. - Help suppliers obtain ISO1400 certifications [55]. - Train supplier employees on environmental issues [54]. - Transfer employees with environmental expertise to suppliers [1].	G1, G3, G5, and G7
Social	- Adopt ethical standards with employees, customers, suppliers, and investors [1]. - Build mutual trust [46]. - Eliminate poor health conditions, gender discrimination, and unfair work practices [54]. - Evaluate suppliers with formally established procedures and standards [46]. - Promote social responsibility in the supply chain [54].	G1, G2, G3, and G4
Economic	- Financial, operational, and technological support [1]. - Formal supplier evaluations and feedback [1]. - Joint development and integration programs to develop new materials and products [5]. - Joint ventures [5]. - Longterm contracts [46]. - Site visits [55].	G1, G2, G5, and G6

4. Application Case Study

4.1. Presentation of the Company

The pilot application of the proposed model was performed in a sugarcane mill. This mill is one of a group of companies located in various states in Brazil. The company in question seeks to continually improve its operations' sustainability through actions involving stakeholders such as suppliers, commercial partners, and the local community. The company has an integrated management system that encompasses quality and environmental management and worker safety. This system contributes to improving internal operations, facilitates supplier integration, and obtains information for DMs.

The company has more than 1400 registered suppliers, most of which are small sugarcane producers located near the mills. It also has international suppliers, which mainly supply fertilizers. The company seeks to work with suppliers aligned with its values of environmental preservation, continual improvement, and social responsibility. It also seeks to strengthen its relationships with its suppliers and develop partnerships with them. The group of mills coordinates various supplier development programs, ranging from training and periodic meetings to exchanging knowledge to implementing continual improvement programs, cost reductions, and improved worker safety.

The firm has an environmental risk prevention program that seeks to make the work environment safer while contributing to preserving the safety of its employees and its suppliers. This program includes training on preventing and controlling the risk of fires in sugarcane fields. The social programs include gathering and distributing clothes and blankets to needy people. Some programs promote education and culture in the sugarcane mills' communities.

To improve the sustainability of its operations and meet the requirements of the international market, the company has obtained a certification from the Environmental Protection Agency. Also, it has a RenovaBio seal, whose objective is to expand the sustainable production of biofuels in Brazil and reduce greenhouse gas emissions. All of the energy produced by this company comes from sugarcane biomass, which is a source of clean and renewable energy. The company produces all the energy consumed by its operations, and the excess energy is commercialized. There are solid waste management programs that ensure the reincorporation of some production wastes (mainly sugarcane bagasse) or their appropriate disposal.

4.2. Application of the Proposed Model

4.2.1. Stage 1: Definition, Training, and Validation of the ANFIS Models

A group of DMs was defined as four company employees who directly participate in supply management: one from the supply department, another from the quality department, an environmental manager, and a work safety engineer. The experience of these DMs ranged from 4 to 9 years in the company. Three meetings were held with the DMs. The first presented the model and defined the criteria. The second defined the suppliers and the collection of their supplier evaluations. The third meeting analyzed the results provided by the model.

Based on this discussion, the DMs opted to: select the criteria that were already used by the company in the supplier evaluation process, which facilitated the obtaining of data to train the model; and adopt three or four criteria for each TBL dimension in order to prioritize the selection of crucial criteria for each dimension.

Initially, one of the authors of this study explained each step of the proposed model to the DMs and clarified their roles in the process. Following this introduction, the DMs engaged in a collaborative discussion to define the supplier segmentation criteria for this pilot application. This discussion was guided by the criteria presented in Table A1 (see Appendix A) and the company's internal supplier evaluation forms. Throughout the deliberation, the DMs carefully considered each potential criterion, evaluating its relevance to supplier performance, alignment with the company's sustainability strategy and broader business objectives, and measurability based on available data. In addition, they sought to ensure a balanced representation of the three TBL dimensions so that no dimension was underrepresented. The DMs debated the relative importance of each criterion, considering the strategic impact on the company. Based on this process, the DMs decided to: (i) select criteria already used in the company's supplier evaluation process, facilitating access to historical data for model training; and (ii) adopt three to four criteria per TBL dimension, prioritizing those most critical for evaluating supplier performance while maintaining a comprehensive and balanced approach. This discussion-based selection process ensured that the chosen criteria were both strategically meaningful and practically applicable.

In total, the DMs selected 12 criteria to evaluate supplier performance. For the environmental dimension (ANFIS 1), they chose the criteria pollution control (C1), environmental management system (C2), resource consumption (C3), and recycling program (C4). For the social dimension (ANFIS 2), they selected employment practices (C5), health and safety (C6), and local community influence (C7). Finally, for the economic dimension (ANFIS 3), the criteria cost (C8), quality (C9), delivery time (C10), flexibility (C11), and technology capability (C12) have been chosen. The DMs have assigned all of these criteria equal weight within each dimension. It should be emphasized that these criteria have been selected just for this application, and future applications can use other criteria that align with each particular company's reality.

For this study, we collected samples containing 200 supplier evaluations. These values were obtained from the performance history of the suppliers. They were extracted by using the supplier evaluation tool within the company's ERP system. The DMs chose to include suppliers essential for achieving the company's sustainable performance. The sample size of 200 supplier evaluations was chosen because it represents a sufficiently broad dataset to demonstrate the segmentation process effectively. This number ensures the inclusion of suppliers across the different groups, which would not be feasible with a tiny sample, as it could compromise the model's ability to classify diverse cases. At the same time, it avoids the impracticality and excessive effort of evaluating the entire supplier base, making the analysis both representative and operationally viable.

The scales utilized varied with the criteria, so each criterion has a specifically defined domain. The values of the criteria C1, C3, C4, and C9 varied between 0 and 100, using a percentage score. For the criteria C2, C5, C6, C7, C8, C10, C11 and C12, the scores ranged from 0 to 10. The output variables (the global performance of the supplier for each TBL dimension) were calculated using the TOPSIS technique based on the collected input data. Table 4 illustrates the obtained supplier score samples for the supervised learning processes for the ANFIS 1 model. The ellipses in the table represent omitted rows of the dataset, showing only a sample of the supplier scores for illustrative purposes.

Table 4. Sample Supplier Scores for the Computational Model 1.

Suppliers	Supplier Scores on Each Criterion (Inputs)				Output (Y1)
	C1	C2	C3	C4	
S1	100	6	48	62	0.5845
S2	93	9	8	51	0.5453
S3	69	2	69	62	0.5024
S4	90	9	59	70	0.6215
S5	76	5	11	94	0.3797
:	:	:	:	:	:
S200	68	6	35	59	0.4987

To perform the supervised learning process for each of the ANFIS models through cross-validation, the samples were separated into two sets. The first set, corresponding to 70% of the samples, was used in the training process. The second set, with 30% of the samples, was reserved for validation. Based on [56], the number of training epochs was 500.

We chose to use only the ANFIS training algorithm because it is an optimized approach capable of simultaneously adjusting the consequents of the rules and the fuzzy sets associated with the input variables. Given that our model required training 108 instances, employing an alternative algorithm would have effectively doubled the number of training (216), substantially increasing computational time and potentially hindering both the implementation of the model and its reproducibility.

The tested topologies for the ANFIS models are presented in Table 5. The topological parameters were defined based on several previous studies that have applied ANFIS to supply chain management problems. To partition the input variables, we tested triangular, trapezoidal, and Gaussian functions [13,22]. We tested linear functions and constant values for the consequent type of the inference rules [21,49]. Regarding the number of input partitions, we tested 3, 4, and 5 [51,56]. Finally, in terms of fuzzy operators for the connectives of the inference rules, we tested the minimum and algebraic product operators [21,49]. We arrived at 108 topologies tested with these procedures, representing 36 for each ANFIS model.

Table 5. Tested Parameters Using Cross-Validation.

Description of the Parameters	Tested Functions and Values
Membership function type: determines the quantitative representation and behavior of input variables.	Triangular, trapezoidal, and Gaussian functions [22,51].
Consequent type: determines the type of the output for each activated rule.	Linear functions and constant values [21,49,50].
Number of fuzzy membership functions: determines the partition granularity of the fuzzy input variables.	3, 4, and 5 functions [51,56].
Fuzzy operator: responsible for aggregation operations among the degrees of activated membership functions.	Minimum and algebraic product operators [21,50].

Tables 6–8 present the results achieved during the computation implementation of the candidate topologies for models ANFIS 1, 2, and 3, respectively. During the training and validation of the candidate topologies, we calculated the MSE values. Based on [21,57], the maximum MSE deemed acceptable for a topology was defined as $\varepsilon = 5 \times 10^{-3}$. The candidate topologies that achieved the most accuracy for each ANFIS model have been highlighted in bold.

The results of the computational implementation of the ANFIS models show that the Gaussian functions performed the best for the three ANFIS models. Topologies of three input partitions produced the best result for two ANFIS models, and using four input partitions produced the best results for the other models. Topologies based on the crisp consequents and the product operator were the ones that achieved the lowest MSEs. Furthermore, the results demonstrate that the lower the number of input variables is, the greater the model's accuracy.

According to Table 6, the topology that achieved the lowest MSE for the ANFIS 1 model was number 36, with an error value during the validation step of 2.380×10^{-4}. For model ANFIS 2, according to Table 7, the best topology was number 64, which achieved an MSE value of 9.769×10^{-6}. Table 8 shows that the best topology for the ANFIS 3 model was number 103, with an error value during the validation step of 2.958×10^{-3}. Most of the topologies that presented the best performance were the candidate topologies for the ANFIS 2 model. This may be explained by the lower number of input variables used in these models. The ANFIS 3 model used five input variables, and its best topology obtained MSE values of magnitude 10^{-3}, while the ANFIS 2 model with just three input variables obtained MSE values of magnitude 10^{-6}. Therefore, since the topologies 36, 64, and 103 presented the best results and attained a satisfactory accuracy (MSE $\leq \varepsilon$), they were selected for application in Stage 2.

Table 6. Results Achieved by the Candidate Topologies for the ANFIS 1 Models.

Candidate Topology	Number of Inference Rules	Membership Function Type	Consequent Type	Number of Fuzzy Membership Functions	Fuzzy Operator	Training MSE	Training RMSE	Validation MSE	Validation RMSE
1	81	Triangular	Crisp	3	Minimum	2.738×10^{-4}	1.654×10^{-2}	3.518×10^{-3}	5.933×10^{-2}
2	81	Triangular	Crisp	3	Product	4.277×10^{-6}	2.068×10^{-3}	3.820×10^{-4}	1.955×10^{-2}
3	256	Triangular	Crisp	4	Minimum	2.719×10^{-11}	5.215×10^{-6}	2.885×10^{-3}	5.371×10^{-2}
4	256	Triangular	Crisp	4	Product	5.659×10^{-12}	2.379×10^{-6}	1.056×10^{-2}	1.028×10^{-1}
5	625	Triangular	Crisp	5	Minimum	8.425×10^{-12}	2.902×10^{-6}	2.641×10^{-2}	1.624×10^{-1}
6	625	Triangular	Crisp	5	Product	3.557×10^{-12}	1.886×10^{-6}	6.540×10^{-2}	2.557×10^{-1}
7	81	Triangular	Linear	3	Minimum	2.597×10^{-15}	5.096×10^{-8}	1.073×10^{-2}	1.036×10^{-1}
8	81	Triangular	Linear	3	Product	5.239×10^{-15}	7.238×10^{-8}	2.269×10^{-3}	4.764×10^{-2}
9	256	Triangular	Linear	4	Minimum	2.606×10^{-15}	5.105×10^{-8}	4.776×10^{-3}	6.911×10^{-2}
10	256	Triangular	Linear	4	Product	6.729×10^{-15}	8.205×10^{-8}	1.058×10^{-2}	1.029×10^{-1}
11	625	Triangular	Linear	5	Minimum	5.544×10^{-15}	7.444×10^{-8}	2.667×10^{-2}	1.633×10^{-1}
12	625	Triangular	Linear	5	Product	8.285×10^{-15}	9.099×10^{-8}	4.669×10^{-2}	2.161×10^{-1}
13	81	Trapezoidal	Crisp	3	Minimum	6.117×10^{-4}	2.473×10^{-2}	4.336×10^{-2}	2.082×10^{-1}
14	81	Trapezoidal	Crisp	3	Product	5.414×10^{-4}	2.326×10^{-2}	1.340×10^{-1}	3.660×10^{-1}
15	256	Trapezoidal	Crisp	4	Minimum	8.607×10^{-6}	2.933×10^{-3}	8.072×10^{-2}	2.840×10^{-1}
16	256	Trapezoidal	Crisp	4	Product	1.028×10^{-9}	3.206×10^{-5}	1.270×10^{-1}	3.564×10^{-1}
17	625	Trapezoidal	Crisp	5	Minimum	1.285×10^{-11}	3.584×10^{-6}	9.416×10^{-2}	3.069×10^{-1}
18	625	Trapezoidal	Crisp	5	Product	6.073×10^{-12}	2.464×10^{-6}	1.321×10^{-1}	3.634×10^{-1}
19	81	Trapezoidal	Linear	3	Minimum	9.499×10^{-15}	9.746×10^{-8}	2.353×10^{-2}	1.534×10^{-1}
20	81	Trapezoidal	Linear	3	Product	1.224×10^{-14}	1.106×10^{-7}	2.769×10^{-2}	1.664×10^{-1}
21	256	Trapezoidal	Linear	4	Minimum	7.910×10^{-14}	2.811×10^{-7}	4.623×10^{-2}	2.150×10^{-1}
22	256	Trapezoidal	Linear	4	Product	6.299×10^{-14}	2.509×10^{-7}	5.915×10^{-2}	2.432×10^{-1}
23	625	Trapezoidal	Linear	5	Minimum	4.237×10^{-14}	2.058×10^{-7}	9.806×10^{-2}	3.131×10^{-1}
24	625	Trapezoidal	Linear	5	Product	4.415×10^{-14}	2.101×10^{-7}	1.183×10^{-1}	3.439×10^{-1}
25	81	Gaussian	Crisp	3	Minimum	8.543×10^{-5}	9.241×10^{-3}	1.428×10^{-3}	3.778×10^{-2}
26	**81**	**Gaussian**	**Crisp**	**3**	**Product**	$\mathbf{2.381 \times 10^{-5}}$	$\mathbf{4.879 \times 10^{-3}}$	$\mathbf{2.380 \times 10^{-4}}$	$\mathbf{1.543 \times 10^{-2}}$
27	256	Gaussian	Crisp	4	Minimum	1.626×10^{-11}	4.032×10^{-6}	1.565×10^{-3}	3.956×10^{-2}
28	256	Gaussian	Crisp	4	Product	1.594×10^{-11}	3.991×10^{-6}	1.032×10^{-2}	1.016×10^{-1}
29	625	Gaussian	Crisp	5	Minimum	8.993×10^{-12}	2.999×10^{-6}	1.198×10^{-2}	1.094×10^{-1}
30	625	Gaussian	Crisp	5	Product	2.690×10^{-12}	1.640×10^{-6}	7.195×10^{-2}	2.682×10^{-1}
31	81	Gaussian	Linear	3	Minimum	1.535×10^{-15}	3.918×10^{-8}	4.037×10^{-3}	6.354×10^{-2}
32	81	Gaussian	Linear	3	Product	1.376×10^{-14}	1.173×10^{-7}	7.782×10^{-3}	8.822×10^{-2}
33	256	Gaussian	Linear	4	Minimum	1.833×10^{-15}	4.281×10^{-8}	3.658×10^{-3}	6.048×10^{-2}
34	256	Gaussian	Linear	4	Product	1.235×10^{-14}	1.111×10^{-7}	1.351×10^{-2}	1.162×10^{-1}
35	625	Gaussian	Linear	5	Minimum	3.656×10^{-15}	6.045×10^{-8}	1.296×10^{-2}	1.138×10^{-1}
36	625	Gaussian	Linear	5	Product	2.567×10^{-14}	1.602×10^{-7}	4.822×10^{-2}	2.196×10^{-1}

Table 7. Results Achieved by the Candidate Topologies for the ANFIS 2 Models.

Candidate Topology	Number of Inference Rules	Membership Function Type	Consequent Type	Number of Fuzzy Membership Functions	Fuzzy Operator	Training MSE	Training RMSE	Validation MSE	Validation RMSE
37	81	Triangular	Crisp	3	Minimum	3.075×10^{-4}	1.754×10^{-2}	5.539×10^{-4}	2.354×10^{-2}
38	81	Triangular	Crisp	3	Product	7.921×10^{-6}	2.814×10^{-3}	1.349×10^{-5}	3.673×10^{-3}
39	256	Triangular	Crisp	4	Minimum	1.063×10^{-4}	1.031×10^{-2}	3.618×10^{-4}	1.902×10^{-2}
40	256	Triangular	Crisp	4	Product	1.697×10^{-6}	1.303×10^{-3}	2.178×10^{-5}	4.667×10^{-3}
41	625	Triangular	Crisp	5	Minimum	8.705×10^{-6}	2.950×10^{-3}	2.077×10^{-2}	1.441×10^{-1}
42	625	Triangular	Crisp	5	Product	2.850×10^{-10}	1.688×10^{-5}	8.717×10^{-3}	9.336×10^{-2}
43	81	Triangular	Linear	3	Minimum	8.052×10^{-7}	8.973×10^{-4}	1.389×10^{-4}	1.179×10^{-2}
44	81	Triangular	Linear	3	Product	9.466×10^{-8}	3.077×10^{-4}	5.206×10^{-5}	7.215×10^{-3}
45	256	Triangular	Linear	4	Minimum	3.210×10^{-14}	1.792×10^{-7}	1.606×10^{-4}	1.267×10^{-2}
46	256	Triangular	Linear	4	Product	4.448×10^{-15}	6.669×10^{-8}	9.201×10^{-5}	9.592×10^{-3}
47	625	Triangular	Linear	5	Minimum	6.219×10^{-16}	2.494×10^{-8}	7.544×10^{-3}	8.686×10^{-2}
48	625	Triangular	Linear	5	Product	1.308×10^{-15}	3.617×10^{-8}	1.153×10^{-2}	1.074×10^{-1}
49	81	Trapezoidal	Crisp	3	Minimum	7.520×10^{-5}	8.672×10^{-3}	1.167×10^{-4}	1.080×10^{-2}
50	81	Trapezoidal	Crisp	3	Product	7.542×10^{-5}	8.684×10^{-3}	1.171×10^{-4}	1.082×10^{-2}
51	256	Trapezoidal	Crisp	4	Minimum	2.845×10^{-4}	1.687×10^{-2}	5.836×10^{-2}	2.416×10^{-1}
52	256	Trapezoidal	Crisp	4	Product	1.105×10^{-4}	1.051×10^{-2}	4.418×10^{-4}	2.102×10^{-2}
53	625	Trapezoidal	Crisp	5	Minimum	1.218×10^{-4}	1.104×10^{-2}	2.826×10^{-1}	5.316×10^{-1}
54	625	Trapezoidal	Crisp	5	Product	1.076×10^{-4}	1.037×10^{-2}	6.911×10^{-2}	2.629×10^{-1}
55	81	Trapezoidal	Linear	3	Minimum	9.025×10^{-7}	9.500×10^{-4}	1.946×10^{-3}	4.411×10^{-2}
56	81	Trapezoidal	Linear	3	Product	1.542×10^{-7}	3.927×10^{-4}	5.054×10^{-4}	2.248×10^{-2}
57	256	Trapezoidal	Linear	4	Minimum	1.836×10^{-13}	4.285×10^{-7}	1.012×10^{-3}	3.181×10^{-2}
58	256	Trapezoidal	Linear	4	Product	7.792×10^{-14}	2.791×10^{-7}	1.052×10^{-3}	3.243×10^{-2}
59	625	Trapezoidal	Linear	5	Minimum	8.016×10^{-8}	2.831×10^{-4}	4.529×10^{-2}	2.128×10^{-1}
60	625	Trapezoidal	Linear	5	Product	8.016×10^{-8}	2.831×10^{-4}	4.978×10^{-2}	2.231×10^{-1}
61	81	Gaussian	Crisp	3	Minimum	7.841×10^{-5}	8.855×10^{-3}	1.242×10^{-4}	1.114×10^{-2}
62	81	Gaussian	Crisp	3	Product	6.943×10^{-6}	2.635×10^{-3}	1.125×10^{-5}	3.354×10^{-3}
63	256	Gaussian	Crisp	4	Minimum	2.093×10^{-5}	4.575×10^{-3}	5.461×10^{-5}	7.390×10^{-3}
64	**256**	**Gaussian**	**Crisp**	**4**	**Product**	$\mathbf{7.844 \times 10^{-7}}$	$\mathbf{8.857 \times 10^{-4}}$	$\mathbf{9.769 \times 10^{-6}}$	$\mathbf{3.126 \times 10^{-3}}$
65	625	Gaussian	Crisp	5	Minimum	5.196×10^{-7}	7.208×10^{-4}	1.142×10^{-1}	3.379×10^{-1}
66	625	Gaussian	Crisp	5	Product	1.194×10^{-9}	3.455×10^{-5}	3.517×10^{-3}	5.930×10^{-2}
67	81	Gaussian	Linear	3	Minimum	7.606×10^{-7}	8.721×10^{-4}	2.097×10^{-4}	1.448×10^{-2}
68	81	Gaussian	Linear	3	Product	1.781×10^{-8}	1.335×10^{-4}	1.088×10^{-4}	1.043×10^{-2}
69	256	Gaussian	Linear	4	Minimum	3.571×10^{-14}	1.890×10^{-7}	5.159×10^{-5}	7.183×10^{-3}
70	256	Gaussian	Linear	4	Product	2.344×10^{-14}	1.531×10^{-7}	8.415×10^{-5}	9.173×10^{-3}
71	625	Gaussian	Linear	5	Minimum	1.448×10^{-15}	3.805×10^{-8}	1.921×10^{-3}	4.383×10^{-2}
72	625	Gaussian	Linear	5	Product	4.698×10^{-15}	6.854×10^{-8}	1.287×10^{-2}	1.134×10^{-1}

Table 8. Results Achieved by the Candidate Topologies in the ANFIS 3 Models.

Candidate Topology	Number of Inference Rules	Membership Function Type	Consequent Type	Number of Fuzzy Membership Functions	Fuzzy Operator	Training MSE	Training RMSE	Validation MSE	Validation RMSE
73	81	Triangular	Crisp	3	Minimum	1.385×10^{-9}	3.720×10^{-5}	9.198×10^{-3}	9.593×10^{-2}
74	81	Triangular	Crisp	3	Product	1.065×10^{-11}	3.264×10^{-6}	8.355×10^{-3}	9.142×10^{-2}
75	256	Triangular	Crisp	4	Minimum	1.542×10^{-11}	3.927×10^{-6}	3.852×10^{-2}	1.962×10^{-1}
76	256	Triangular	Crisp	4	Product	2.761×10^{-12}	1.661×10^{-6}	1.358×10^{-1}	3.685×10^{-1}
77	625	Triangular	Crisp	5	Minimum	3.018×10^{-11}	5.495×10^{-6}	1.183×10^{-1}	3.439×10^{-1}
78	625	Triangular	Crisp	5	Product	3.212×10^{-12}	1.791×10^{-6}	2.199×10^{-1}	4.690×10^{-1}
79	81	Triangular	Linear	3	Minimum	6.159×10^{-16}	7.846×10^{-8}	1.215×10^{-2}	1.102×10^{-1}
80	81	Triangular	Linear	3	Product	5.302×10^{-16}	7.282×10^{-8}	1.175×10^{-2}	1.084×10^{-1}
81	256	Triangular	Linear	4	Minimum	9.885×10^{-16}	9.943×10^{-8}	4.131×10^{-2}	2.031×10^{-1}
82	256	Triangular	Linear	4	Product	6.336×10^{-15}	7.958×10^{-8}	6.981×10^{-2}	2.641×10^{-1}
83	625	Triangular	Linear	5	Minimum	2.984×10^{-15}	5.462×10^{-8}	1.165×10^{-1}	3.414×10^{-1}
84	625	Triangular	Linear	5	Product	2.704×10^{-15}	5.200×10^{-8}	1.551×10^{-1}	3.938×10^{-1}
85	81	Trapezoidal	Crisp	3	Minimum	2.777×10^{-05}	5.267×10^{-3}	8.711×10^{-2}	2.950×10^{-1}
86	81	Trapezoidal	Crisp	3	Product	1.101×10^{-05}	3.318×10^{-3}	6.174×10^{-2}	2.484×10^{-1}
87	256	Trapezoidal	Crisp	4	Minimum	4.329×10^{-12}	2.080×10^{-6}	1.829×10^{-1}	4.277×10^{-1}
88	256	Trapezoidal	Crisp	4	Product	1.545×10^{-12}	1.243×10^{-6}	2.093×10^{-1}	4.576×10^{-1}
89	625	Trapezoidal	Crisp	5	Minimum	2.511×10^{-7}	5.011×10^{-4}	2.033×10^{-1}	4.509×10^{-1}
90	625	Trapezoidal	Crisp	5	Product	2.510×10^{-7}	5.010×10^{-4}	2.398×10^{-1}	4.897×10^{-1}
91	81	Trapezoidal	Linear	3	Minimum	9.025×10^{-15}	9.497×10^{-8}	5.713×10^{-2}	2.390×10^{-1}
92	81	Trapezoidal	Linear	3	Product	8.604×10^{-15}	9.272×10^{-8}	6.371×10^{-2}	2.523×10^{-1}
93	256	Trapezoidal	Linear	4	Minimum	1.327×10^{-14}	1.152×10^{-7}	1.783×10^{-1}	4.221×10^{-1}
94	256	Trapezoidal	Linear	4	Product	2.253×10^{-14}	1.500×10^{-7}	1.936×10^{-1}	4.398×10^{-1}
95	625	Trapezoidal	Linear	5	Minimum	1.427×10^{-14}	1.194×10^{-7}	2.023×10^{-1}	4.497×10^{-1}
96	625	Trapezoidal	Linear	5	Product	8.294×10^{-15}	9.102×10^{-8}	2.257×10^{-1}	4.751×10^{-1}
97	81	Gaussian	Crisp	3	Minimum	5.132×10^{-10}	2.266×10^{-5}	4.202×10^{-3}	6.484×10^{-2}
98	81	Gaussian	Crisp	3	Product	1.453×10^{-11}	3.811×10^{-6}	1.680×10^{-2}	1.296×10^{-1}
99	256	Gaussian	Crisp	4	Minimum	2.169×10^{-11}	4.657×10^{-6}	1.340×10^{-2}	1.157×10^{-1}
100	256	Gaussian	Crisp	4	Product	1.657×10^{-12}	1.287×10^{-6}	1.482×10^{-1}	3.850×10^{-1}
101	625	Gaussian	Crisp	5	Minimum	3.195×10^{-11}	5.650×10^{-6}	6.921×10^{-2}	2.630×10^{-1}
102	625	Gaussian	Crisp	5	Product	1.295×10^{-12}	1.138×10^{-6}	2.443×10^{-1}	4.943×10^{-1}
103	**81**	**Gaussian**	**Linear**	**3**	**Minimum**	$\mathbf{2.978 \times 10^{-16}}$	$\mathbf{1.726 \times 10^{-8}}$	$\mathbf{2.958 \times 10^{-3}}$	$\mathbf{5.436 \times 10^{-2}}$
104	81	Gaussian	Linear	3	Product	1.556×10^{-14}	1.247×10^{-7}	1.383×10^{-2}	1.176×10^{-1}
105	256	Gaussian	Linear	4	Minimum	9.274×10^{-16}	9.629×10^{-8}	1.391×10^{-2}	1.179×10^{-1}
106	256	Gaussian	Linear	4	Product	1.584×10^{-14}	1.258×10^{-7}	6.808×10^{-2}	2.608×10^{-1}
107	625	Gaussian	Linear	5	Minimum	2.448×10^{-15}	4.948×10^{-8}	4.646×10^{-2}	2.155×10^{-1}
108	625	Gaussian	Linear	5	Product	1.723×10^{-14}	1.312×10^{-7}	1.536×10^{-1}	3.920×10^{-1}

4.2.2. Stage 2: Application of the ANFIS Models

Stage 2 began with defining which suppliers would be segmented using the tuned ANFIS models. It was decided that the same suppliers would be included in the validation set. The DMs made this choice for the following reasons: all of these suppliers provide relevant goods and/or services to the company in question; since the scores of these suppliers have already been obtained in Step 1.4, the use of these supplier score samples contributed to giving the pilot application more agility. Therefore, 60 suppliers were considered in Stage 2. The scores of these suppliers in each criterion were input into the trained ANFIS models to obtain the predicted values for supplier performance for each TBL dimension. Figure 5a–c illustrate the values predicted by the ANFIS models and the expected values for each supplier. In general, the predicted values for most of the samples were very close. Since the predicted and expected values were practically identical in some cases, there was an overlap of points that prevented the visualization of the marker that indicates the expected values. This occurred mainly in Figure 5b, because the ANFIS 2 model was the one that presented the highest accuracy among all of the computational models developed for this study. In order to illustrate the effect of the training and the inference process for the ANFIS models, Figure 6 presents part of the 81 decision-making rules for Topology 26 (ANFIS 1 model) before the training processes. In contrast, Figure 7 presents the same rules after the training.

In Figures 6 and 7, the first four columns represent the input variables and the last column represents the output variable. The vertical lines in red represent input values, and the parts in yellow represent activated rules. The contribution of each activated rule is represented by the navy blue color in the last column. To illustrate the inference process, we used the input values C1 = 50, C2 = 5, C3 = 50, and C4 = 50 in this model. Since the consequents of the inference rules in Figure 6 have not been adjusted yet, the output value for each rule was 0. Before training, 8 rules were activated, namely rules 14, 32, 38, 41, 42, 44, 50, and 68, generating an output value of 0. After training, with the adjustment in the decision-making rules, 14 rules were activated, namely rules 5, 14, 29, 31, 32, 33, 38, 40, 41, 4, 44, 50, 59, and 68, which achieved an output value of 0.503.

In Figure 7, in addition to the changes in the values of the consequents for each rule, we can also observe the effect of changes in the format of some pertinent functions after training. These changes are more evident in the first two functions of C2 ("environmental management system"). Thus, when suppliers have an environmental management system with "low" or "medium" performance, this will influence the Y1 results more strongly than if they were in other environmental criteria with "low" or "medium" performances. This demonstrates the great relevance of this criterion in terms of supplier environmental performance.

In order to show the relationships between some of the input variables and the output variable for each ANFIS model, Figure 8a–c show the response surface graphs produced after training the ANFIS models. In Figure 8b, it is possible to visualize that Criteria C5 (employment practices) and C7 (local community influence) have a linear relationship with the output variable Y2 if the value of one of these criteria is null. In these cases, an increase in the values of these criteria produces a proportional increase in the value of Y1. On the other hand, in Figure 8c it is possible to verify a nonlinear relationship between C9 (quality) and Y3. If a supplier achieves "high" performance in quality, the value of Y2 will increase substantially. This indicates that the criterion is very relevant to economic performance.

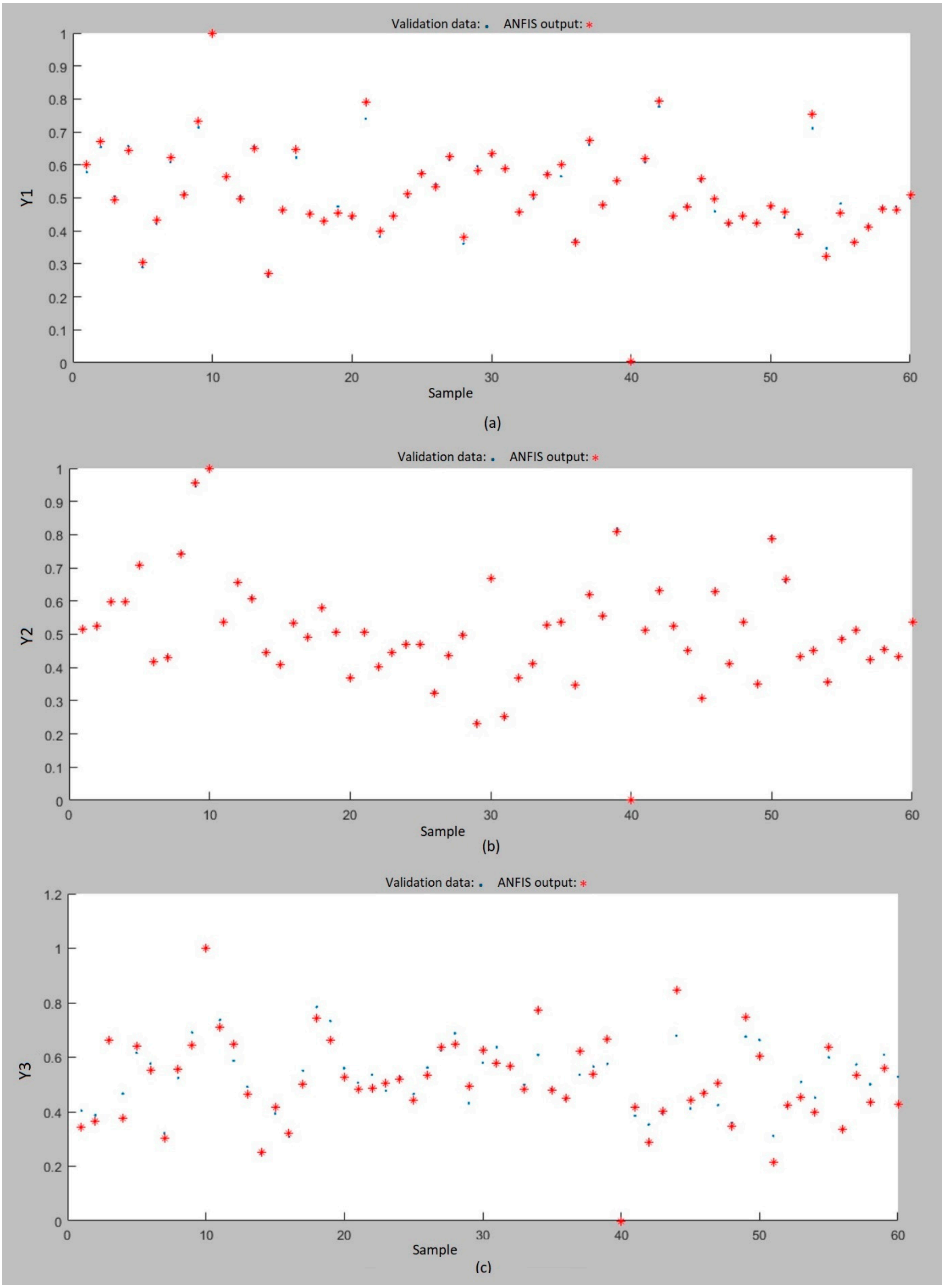

Figure 5. Comparison of the Predicted Values with the Expected Values for the (**a**) ANFIS 1, (**b**) ANFIS 2, (**c**) ANFIS 3 Models.

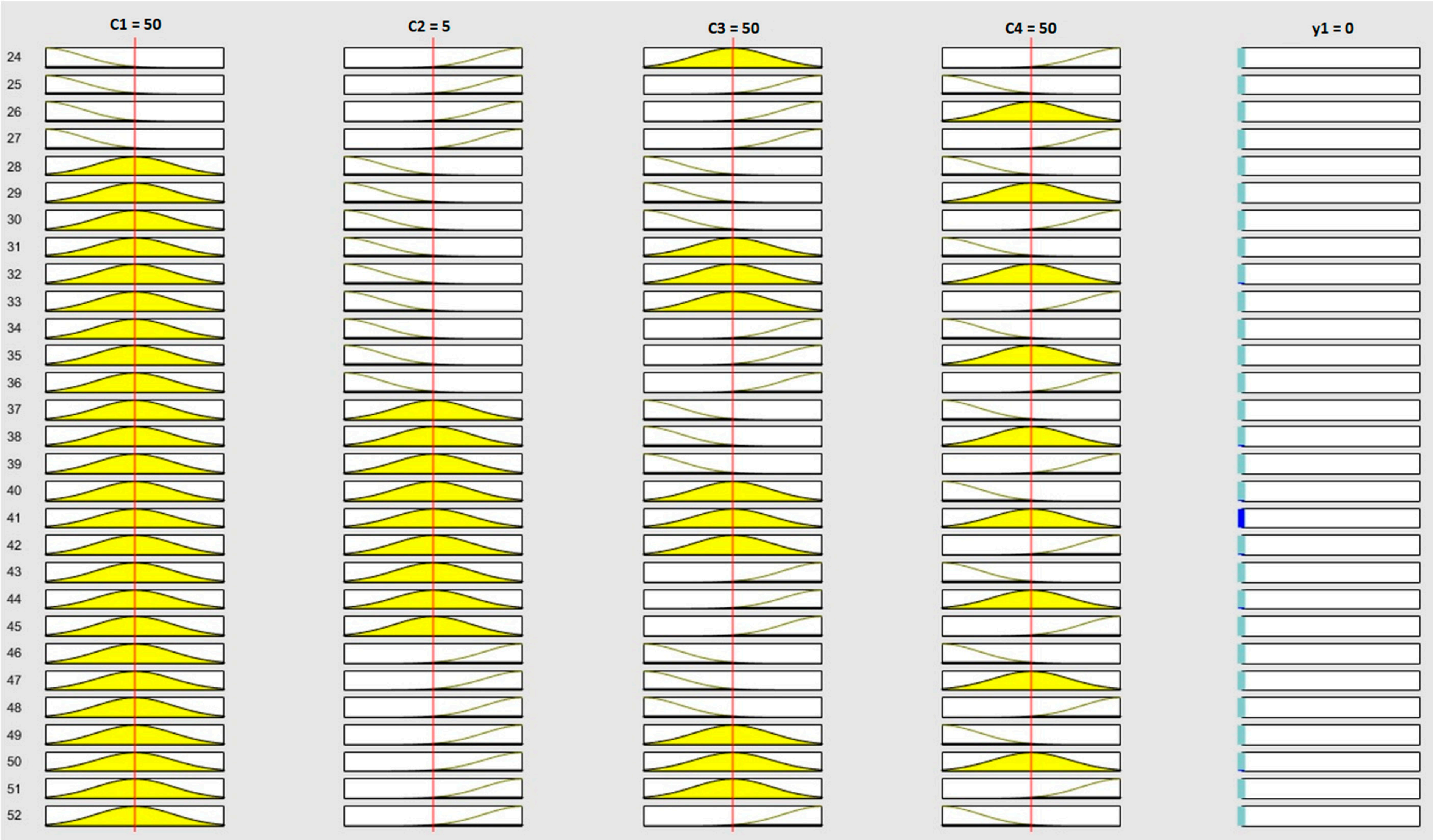

Figure 6. Decision-Making Rules for Candidate Topology #26 before Training.

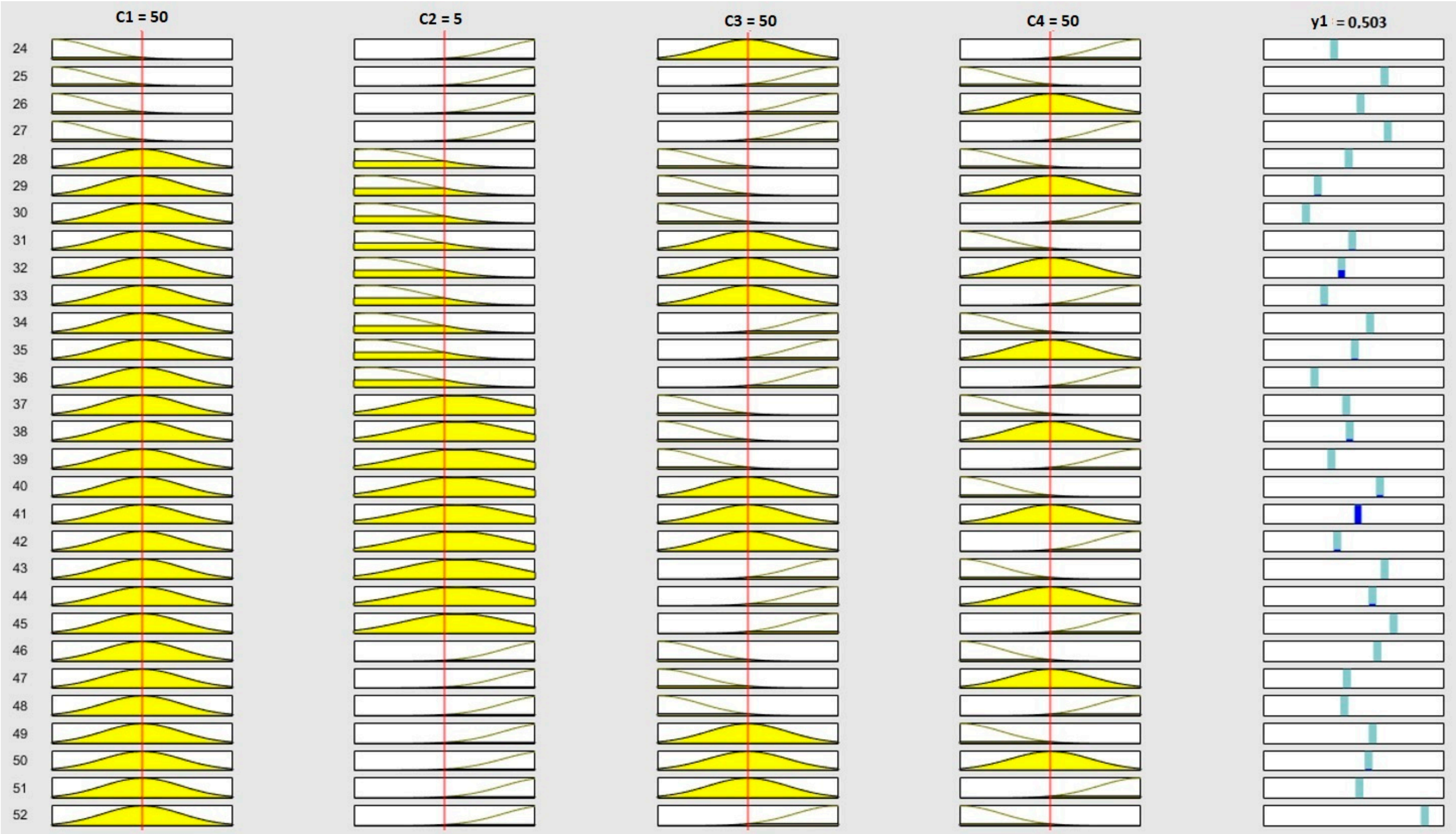

Figure 7. Decision-Making Rules for Candidate Topology #26 after Training.

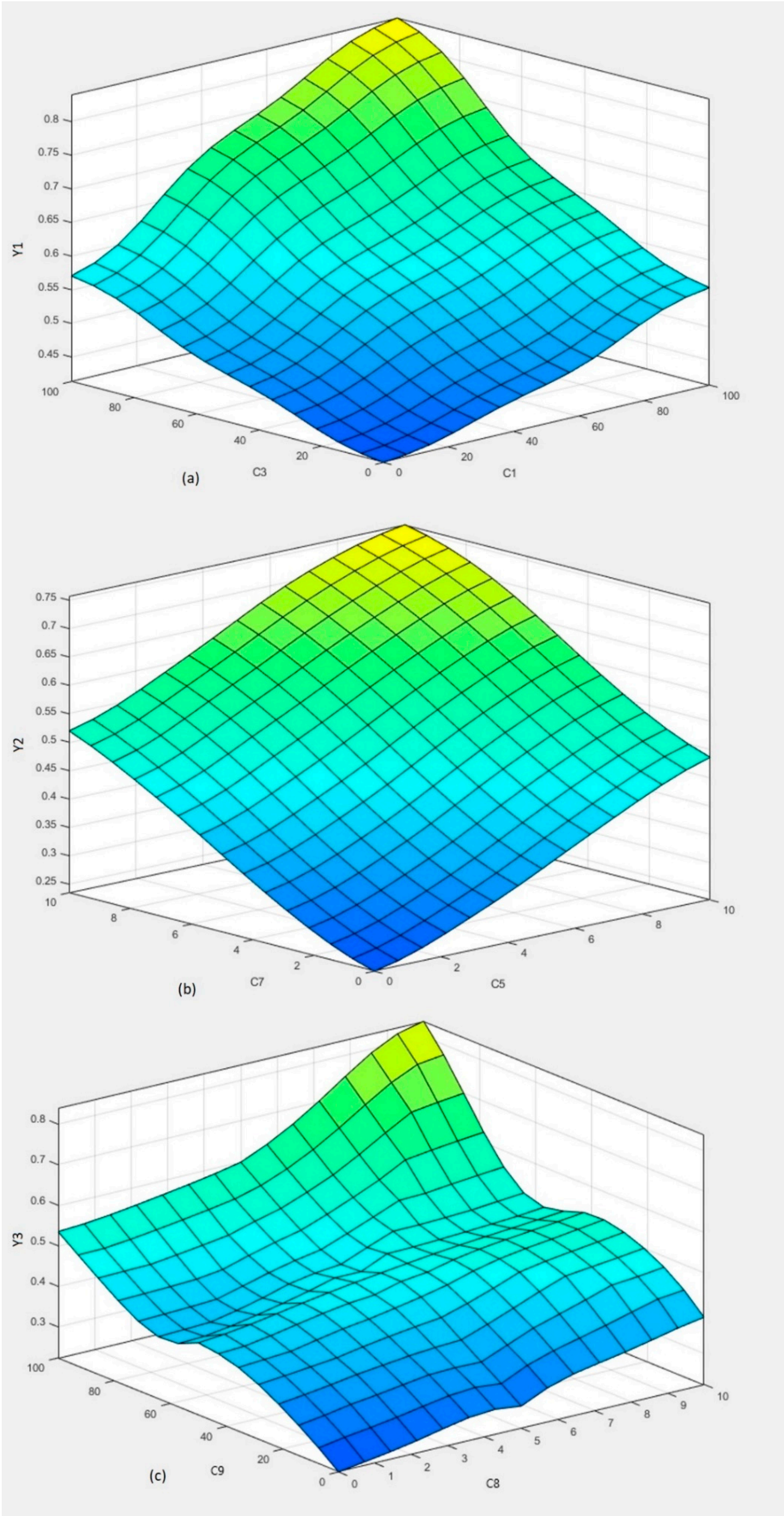

Figure 8. Response Surface Plots of the (**a**) ANFIS 1, ANFIS 2 (**b**), and ANFIS 3 (**c**) Models.

4.2.3. Stage 3: Supplier Categorization

The last step in applying the proposed model is segmenting the suppliers based on the performance values obtained for each ANFIS model in Step 2.3. Threshold values for all of the dimensions were set at 0.5 by the DMs. Figure 9 presents the results of classifying the 60 suppliers evaluated in the previous stage. To improve the visualization of the suppliers in each quadrant, the matrix has been separated into two parts.

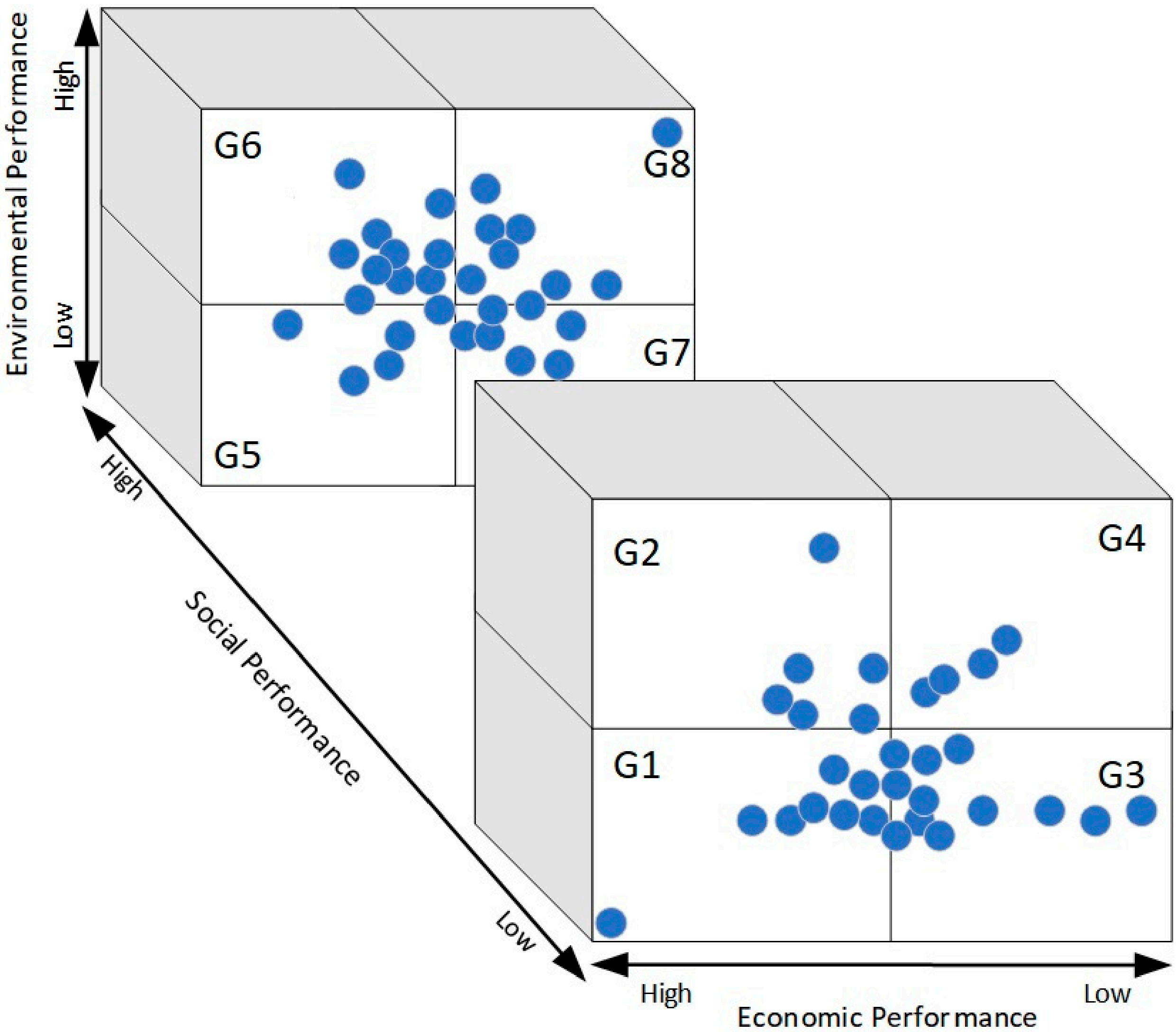

Figure 9. Final Supplier Classification.

The results presented in Figure 9 indicate that eight suppliers were classified in Group 1 because of their poor performance in all of the matrix's dimensions. If it is not possible to substitute the suppliers in this group, some strategies can be applied to improve their economic, environmental, and social development. Six suppliers were classified in Group 2, and the classification results suggest applying strategies to improve their economic and social development. Twelve suppliers classified in Group 3 need strategies to improve their social and environmental development. For Group 4, there were four suppliers whose social performance needs to be improved. For Group 5 there were five suppliers, and they need strategies to improve their economic and environmental development. For Group 6, there were ten suppliers in need of economic development strategies, and for Group 7, there were seven suppliers in need of environmental development strategies. Finally, there are eight suppliers classified in Group 8. These suppliers are the best in the supplier database because they meet the buying company's environmental, social, and economic requirements.

The results of the supplier classification in the segmentation matrix were endorsed and enriched by the DMs, who not only validated the outcomes but also provided interpretive feedback and suggested practical development strategies for each group. For example, supplier S5 was classified in Group 7 as having poor performance in the environmental dimension, mainly in the environmental management system (C2) and resource consumption (C3) criteria. In this case, the DMs recommended assisting the supplier in obtaining Environmental Management System certification. Similarly, supplier S30 was classified in Group 4 due to low performance in all social criteria. This led the DMs to suggest actions such as eliminating poor health conditions and adopting ethics standards with employees, customers, suppliers, and investors. This interaction ensured that the classification results were consistent with the model and aligned with the company's strategic objectives.

Finally, with the suppliers separated into the proposed segmentation matrix, DMs proposed specific strategies for each group to increase their sustainability performance. Based on the result analysis and discussions with the DMs, some possible development programs were indicated for each group. Table 3 served as the basis for defining these programs. For example, supplier S5 was classified in the G7 group and presented poor performance in the environmental dimension. This supplier performed poorly on the environmental management system (C2) and resource consumption (C3) criteria. In this case, the DMs have recommended a strategy in which they "help suppliers to obtain ISO1400 certification". The supplier S30 was classified in the G4 group, with poor performance in the social dimension. Since this supplier achieved low scores in all social criteria, the DMs have suggested applying strategies such as "eliminate poor health conditions" and "adopt ethics standards with employees, customers, suppliers, and investors". Therefore, when choosing one or more strategies, consider the group in which the supplier has been classified, and consider the criteria where they are underperforming.

4.3. Contributions and Implications

The proposed model has some advantages in relation to previous supplier segmentation models. Unlike most of the models displayed in Table 2, the proposed model allows the classification of suppliers according to each TBL dimension to support improving supplier sustainability. In comparison with the models for sustainable supplier segmentation proposed by [6,10,11,13–15], the proposed approach has the advantage of not performing any compensation between the performance dimensions. In this way, when the performance of a supplier in one dimension is low, even if this same supplier has high performance in two of the TBL dimensions, the final result will point to a performance gap. Thus, the model contributes to identifying suppliers with performance gaps while also aiding in achieving a balance among environmental, social, and economic performance.

Like the supplier segmentation models based on AHP [10,26,44,47]; ANP [12], BWM [46], fuzzy logic [13,24,29,31,37,39], and rough sets [2], the proposed model is appropriate for dealing with decision-making processes under uncertainty. However, unlike techniques based on paired comparisons, such as AHP, ANP, and Fuzzy AHP, the proposed model does not limit the number of suppliers that can be evaluated simultaneously.

Another benefit is that using ANFIS models makes it possible to predict supplier performance values accurately for each TBL dimension. The accuracy values achieved by the best topologies were in keeping with the findings of other studies that apply ANFIS models for supply chain management. For example, ref. [50] had higher MSE values with a magnitude of 10^{-2}, while [21] achieved lower error values with an MSE value close to a magnitude of 10^{-4}.

Regarding computational complexity, the complexity of the ANFIS models developed for supplier segmentation is primarily determined by the number of input variables and fuzzy partitions assigned to each input. Each combination of input partitions corresponds to a unique decision rule, directly affecting the number of computations during the training. Despite this exponential growth in rules with respect to inputs and partitions, the models developed in this study have relatively low computational complexity due to the deliberate limitation of 3 to 5 input criteria per model. Model 1 includes 81 fuzzy if-then rules; Model 2 has 64 rules; and Model 3 has 243. Significantly, the number of suppliers does not affect the number of rules, meaning that the models can handle large supplier datasets without a considerable increase in computational processing time.

For scaling to larger or more complex problems, the methodology can be extended by creating additional ANFIS models, each handling a subset of criteria, thereby preventing a combinatorial explosion of rules and preserving convergence during training. By maintaining a controlled number of inputs per model, ANFIS balances interpretability, predictive power, and computational efficiency, making it suitable for large-scale supplier segmentation tasks and enabling its application to hundreds or even thousands of problems with large supplier datasets.

Finally, it is important to highlight that in our study, all ANFIS topologies converged successfully within 500 training epochs. Several factors contributed to this convergence, including the limited number of input criteria per model, the resulting number of decision rules, and the sufficiently large set of training samples used. However, convergence cannot be universally guaranteed. Suppose a model includes a vast number of input variables or an excessive number of fuzzy partitions. In that case, the resulting explosion in the number of decision rules can make convergence more difficult, increase training time, and potentially prevent the algorithm from reaching an optimal solution. Therefore, carefully selecting input criteria and partition granularity is critical to maintain convergence and computational feasibility.

5. Statistical Test Results

Linear regression tests were performed to analyze the relationship between the expected output variables and the values predicted by the best topologies. The R^2 coefficient was calculated to verify the dependent relationship of the y variable (predicted values) with the independent x variable (expected values). R^2 represents the square of the correlation coefficient. The closer it is to 1, the better the model is adjusted to represent the dependent relationship between the input and output variables [58].

Figure 10a–c show the expressions that indicate the relationships between the x and y variables, the values of R^2, and the results of the regression tests performed in Microsoft Excel. The values obtained for R^2 were 0.9905, 0.9996, and 0.8872 for the ANFIS 1, 2, and 3 models, respectively. The predicted values for the ANFIS models are very close to the expected values (validation set). However, the ANFIS 3 model presented the poorest performance among the three analyzed models. This is because it has the most significant number of input variables and, therefore, a larger number of inference rules, which implies a more significant number of parameters to be adjusted during the training, directly interfering with the model's accuracy.

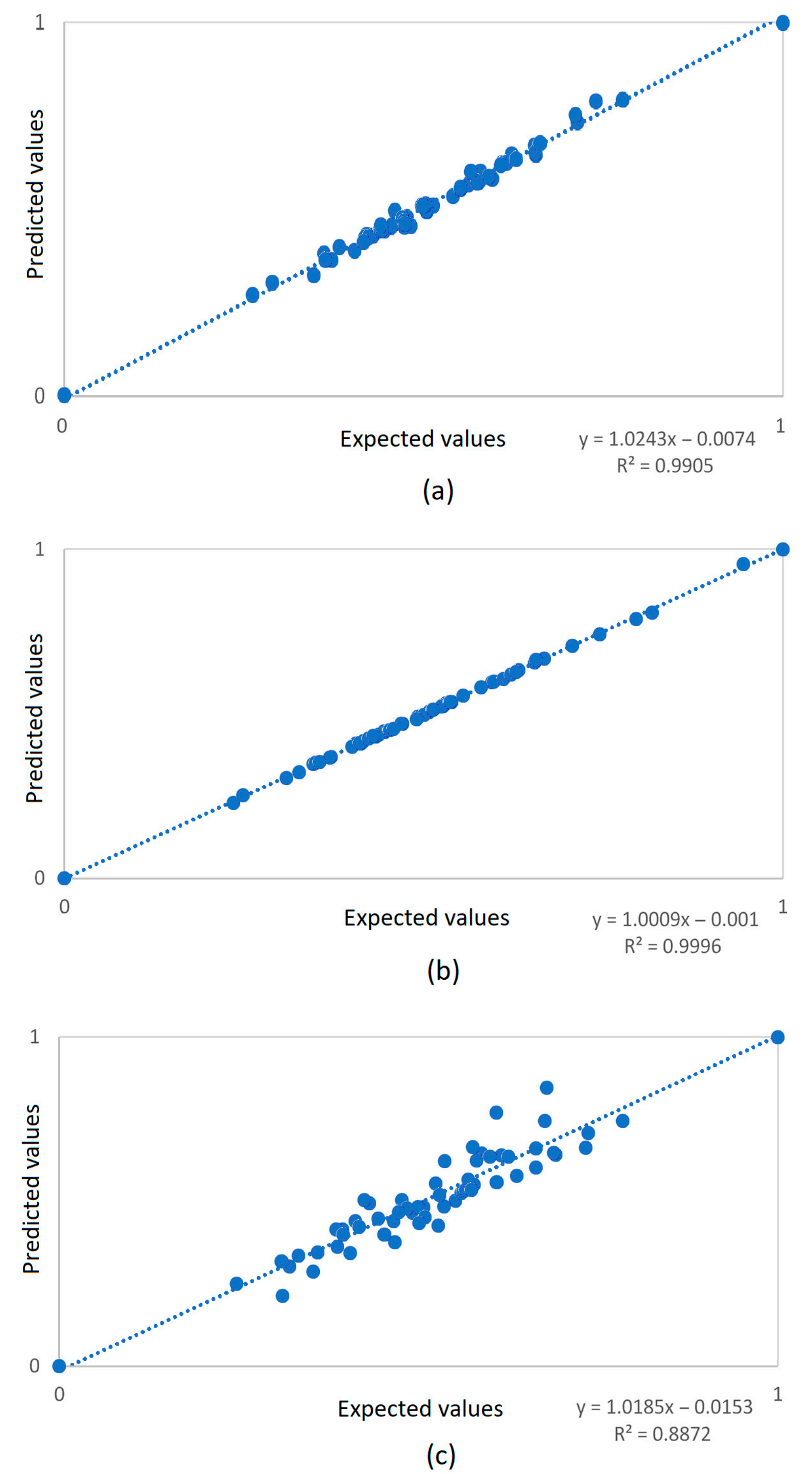

Figure 10. Results of the Linear Regressions Using the ANFIS 1 (**a**), 2 (**b**), and 3 (**c**) Model Results.

To verify whether there is a significant difference between the expected and predicted values using the ANFIS models, we performed three paired *t*-tests. According to [58], this type of test is appropriate when the population data is collected in pairs. Table 9 demonstrates the acceptance and rejection criteria for the null hypothesis with a significance level of α.

Table 9. Statistical Acceptance and Rejection Criteria for the Null Hypothesis.

Null hypothesis:	H_0: $\mu_D = \Delta_0$
Alternative hypothesis:	H_1: $\mu_D \neq \Delta_0$
Test statistic:	$T_0 = \frac{\overline{D}-\Delta_0}{S_D/\sqrt{n}}$
Rejection region (for two-tailed test):	$t_0 < -t_{\alpha/2,n-1}$ or $t_0 > t_{\alpha/2,n-1}$
Reject H_0 if the *p*-value is $<\alpha$	

To perform the *t*-tests, the samples must fulfill the requirements of a normal distribution and homogeneity of the variances among the groups [58]. The normality and homogeneity tests of the variances were performed using the SPSS Statistics software (V22.0) with groups of 60 samples for each validation step of the three ANFIS models. The significance level of $\alpha = 0.01$ was defined for rejecting the null hypothesis, considering the null hypothesis to be that the sample comes from a normal distribution and the alternative hypothesis to be that the sample does not come from a normal distribution. Table 10 presents the results of the normality tests for the six groups of samples, with two for each ANFIS model.

Table 10. Normality Test Results.

Model	Sample Set	Shapiro–Wilk	
		Statistic	*p*-Value
ANFIS 1	Expected values	0.984	0.629
	Predicted values	0.975	0.252
ANFIS 2	Expected values	0.965	0.087
	Predicted values	0.965	0.087
ANFIS 3	Expected values	0.993	0.982
	Predicted values	0.993	0.976

As displayed in Table 10, the data's normality was calculated based on the Shapiro–Wilk (S-W) Test. This test is recommended for samples where $4 < n < 2000$ [58]. The analysis of the test results was performed based on their *p*-values. Taking into account a level of significance of $\alpha = 0.01$ and considering that all of the cases presented *p*-values $> \alpha$, the null hypotheses of the six sample groups were accepted, or in other words, all of the sample groups in Table 10 come from a normal distribution.

To verify the homogeneity of the variances among the groups, we performed Levene's Test utilizing the SPSS Statistics software. Compared to other tests of homogeneity, such as Hartley's Test or the Cochran Test, Levene's Test is more sensitive to deviations from normality and is considered the most robust of these tests [58]. Table 11 presents the results achieved by the samples for the ANFIS models for the homogeneity of variance test. With observed *p*-values of 0.728, 0.990, and 0.423, values which are greater than $\alpha = 0.01$, the test results indicate that the null hypothesis cannot be rejected. Thus, we can conclude that with a confidence level of 99%, the variances are homogeneous.

Table 11. Results of the Homogeneity of Variance Test.

Model	Levene Statistic	*p*-Values
ANFIS 1	0.122	0.728
ANFIS 2	0.000	0.990
ANFIS 3	0.568	0.453

Given that the normality and homogeneity of the variance requirements have been achieved, we can apply the *t*-test. Table 12 presents the results of the *t* tests performed using the SPSS Statistics software. In addition to the significance levels, Table 12 shows the mean differences between the pairs of each sample group, the standard deviation, the mean standard error, the confidence level of the difference, and the calculated t value. Considering a significance level of $\alpha = 0.01$, with the p-values being 0.012, 0.216, and 0.404 for the ANFIS 1, 2, and 3 models, respectively, we cannot reject the null hypotheses. Therefore, we conclude that there are no statistically significant differences between the expected and predicted values. This reinforces the accuracy of the proposed models and the appropriateness of utilizing ANFIS in sustainable supplier segmentation.

Table 12. Results of the Paired-Sample Tests.

Model	Mean	Standard Deviation	Mean Standard Error	T	p-Value
ANFIS 1	−0.00493	0.01473	0.0019	−2.593	0.012
ANFIS 2	0.00051	0.00313	0.0004	1.251	0.216
ANFIS 3	0.00592	0.05455	0.00704	0.841	0.404

6. Conclusions

This study proposed and applied an ANFIS-based model for sustainable supplier segmentation. The implementation and evaluation of 108 ANFIS topologies have made it possible to identify the most suitable values for the internal parameters of the models. The models achieved satisfactory accuracy, with the best topologies identified for each case: topology 36 for ANFIS 1 with MSE = 2.380×10^{-4}, topology 64 for ANFIS 2 with MSE = 9.769×10^{-6}, and topology 103 for ANFIS 3 with MSE = 2.958×10^{-3}. The values obtained for R^2 were 0.9905, 0.9996, and 0.8872 for the ANFIS 1, 2, and 3 models, respectively. The t-tests confirmed no statistically significant differences between the expected and predicted values (p-values = 0.012, 0.216, and 0.404 for ANFIS 1, 2, and 3, respectively, considering $\alpha = 0.01$).

In addition to the benefits discussed in Section 4.3, this proposal presents the following contributions to the supplier segmentation literature:

i. Model based on supervised learning and nonlinear modeling: Using a supervised learning method, this is the first supplier segmentation model that uses historical performance data to automatically adjust the relationships between the input variables, capturing nonlinear interactions among criteria.
ii. Transparency and interpretability through decision rules: The supervised learning process allows the incorporation of available knowledge about supplier performance into the inference rules. This makes the outputs produced by the ANFIS models easily interpretable and allows identification of which decision rules produced specific results.
iii. Identification of appropriate ANFIS topological parameters: This study also contributes by determining appropriate topological parameters to achieve accurate results. These guidelines provide practical support for researchers and practitioners developing computational solutions based on ANFIS for supplier evaluation, ensuring computational efficiency.

Nevertheless, the study has limitations that should be acknowledged. The classification threshold between high and low performance groups remains a subjective choice that depends on each buying company's priorities and strategic positioning. Moreover, the computational complexity of ANFIS increases exponentially with the number of input variables and partitions, which restricts the number of criteria that can be simultaneously considered in a single model. Although the current design with 3 to 5 criteria per model maintains relatively low complexity and reliable convergence, scaling to problems with more than approximately 15 criteria would require the development of additional ANFIS models to avoid rule explosion and convergence issues.

Another limitation is that only one training algorithm was tested in the cross-validation process. This choice was made because the selected algorithm is the most frequently applied in ANFIS training and has achieved satisfactory accuracy in prior studies. Given that our model required training 108 instances, employing an alternative algorithm would have effectively doubled the number of training processes, substantially increasing computational time and potentially hindering both the implementation of the model and its reproducibility in future studies. Future studies could investigate alternative training algorithms to evaluate their impact on model performance and efficiency. It could also conduct comparative analyses of different segmentation models and apply the proposed approach in companies across diverse economic sectors within the TBL context.

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Abbreviations

AHP	Analytic Hierarchy Process
ANFIS	Adaptive Network-based Fuzzy Inference System
ANP	Analytic Network Process
BWM	Best Worst Method
C_j	*j*-th criterion
DEA	Data Envelopment Analysis
DEMATEL	Decision Making Trial and Evaluation Laboratory
DM	Decision Maker
ELECTREE	ÉLimination Et Choix Traduisant la REalité (em francês)
MAUT	Multi-attribute Utility Theory
MCDM	Multi-criteria Decision Making
MSE	Mean Squared Error
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
RMSE	Root Mean Square Error
S_i	*i*-th supplier
TBL	Triple Bottom Line
TOPSIS	Technique for Order of Preference by Similarity to the Ideal Solution
VIKOR	VIsekriterijumska Optimizacija I KOmpromisno Resenje
Y_m	Output of the *m*-th model

Appendix A

Table A1. List of criteria suggested for sustainable supplier segmentation.

Economic Criteria	Environmental Criteria	Social Criteria
- Price	- Pollution control	- Human resources practices
- Cost reduction activities	- Remediation	- Disciplinary and safety practices
- Compliance with pricing behavior	- Endofpipe controls	- Employment contracts
- Conformance quality	- Pollution prevention	- Equality in labor sourcing
- Delivery consistency	- Product adaptation	- Diversity
- Quality philosophy	- Process adaptation	- Discrimination
- Quick response	- Environmental system management	- Employment opportunities
- Time	- Establishment of environmental commitment and policy	- Flexible work arrangements
- Delivery speed	- Identification of environmental aspects	- Employment compensation
- Product development time	- Planning of environmental objectives	- Research and development
- Partnership formation time	- Assignment of environmental responsibility	- Career development
- Flexibility	- Verification and evaluation of environmental activities	- Child labor
- Changes in product volume	- Resource consumption	- Health and safety
- Short setup time	- Water consumption	- Health and safety incidents
- Conflict resolution	- Raw material consumption	- Health and safety practices
- Innovation	- Energy consumption	- Working conditions
- Launch of new products	- Pollution production	- Influence on the local community
- Use of new technologies	- Emission of pollutants	- Health
- Culture	- Production of toxic products	- Education
- Appropriate strategies	- Waste generation	- Housing
- Sense of trust		- Service infrastructure
- Technological compatibility		- Mobility infrastructure
- Technical capability		- Public and regulatory services
- Manufacturing facilities		- Support for educational institutions
- Supplier design capability		- Security
- Longterm relationship		- Growth of economic wellbeing
- Open communication		- Social cohesion
- Reputation for integrity		- Support for community projects
- Relationship closeness		- Stakeholder influence
		- Consumer education
		- Stakeholder engagement
		- Potential for decisionmaking influence

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