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An Adaptive Fuzzy Multi-Criteria Model for Sustainability Assessment of Sugarcane Agroindustry Supply Chain

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ABSTRACT Supply chain sustainability assessment is key to maintaining and improving the performance of agroindustry supply chains, particularly in sustainable agroindustry development. The assessment of agro-industrial supply chain performance is a complex and dynamic process. Hence, there is a need for an adaptive fuzzy multi-criteria sustainability assessment model as an alternative method of analysis and improvement. This study aimed to design an adaptive fuzzy multi-criteria sustainability assessment and improvement model for the sugarcane agroindustry supply chain. In this study: (1) a fuzzy inference system (FIS) was developed to assess the performance of the sustainability dimensions. This study proposed 24 indicators for four dimensions: economic, social, environmental, and resource. (2) An adaptive neuro-fuzzy inference system (ANFIS) is designed to aggregate the overall supply chain sustainability performance. (3) The proposed fuzzy multi-criteria assessment model was compared with the common multidimensional scaling (MDS) and linear models. This study proved that the proposed synthesis of the FIS and ANFIS models is powerful and adaptive for evaluating supply chain sustainability and providing accurate results. (4) The strategies to improve sustainability performance were developed using the cosine amplitude method (CAM). The proposed model determined that the overall supply chain sustainability value was 68.58%, which was almost sustainable. Several strategies have been suggested to improve sustainability performance, including maintaining the sugarcane supply by strengthening the partnership program and improving the mill's overall recovery, followed by factory revitalization or new factory investment.

INDEX TERMS Sustainable development, food industry, fuzzy logic, adaptive algorithm, supply chain management.

I. INTRODUCTION

Sustainable development has been recognized as a global agenda and defined as "developments that meet the needs of the present without compromising the ability of future generations to meet their own needs" [1]. Currently, owing to the challenges faced by humans and the adoption of Industry 4.0, the United Nations has resolved to fully implement sustainable development goals (SDGs) by 2030 [2]. Consequently, SDGs have been implemented in many areas, including country and regional sustainability [3], [4], industrial development [5], [6], small medium enterprises [7], food processing and manufacturing [8], city infrastructure [9], industry, and fresh-cut vegetables [10]. Owing to the adoption of Industry 4.0, which supports the implementation of sustainable development [11], [12], there is a need for sustainability assessment and evaluation for industry. Sustainability implementation in the industry is not only mandatory to achieve Industry 4.0, but also to maintain customer trust and satisfaction [13].

Industrial development is mainly driven by supply chain management (SCM). Sustainability adoption in SCM

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helps maintain performance, stakeholder coordination, and customer satisfaction. Sustainable supply chains have garnered much interest from researchers and industrial practitioners to enhance this approach [14], and improvements in the outcome and goal of the supply chain are recommended [15]. According to one study [16], a sustainable supply chain is a concept for managing information, material, and cash flow through collaboration and information sharing among stakeholders to achieve supply chain goals and compromise with the balance of economic, social, and environmental dimensions. This study proposes supply chain sustainability performance using multi-criteria assessment for agroindustry to ensure performance, adopt Industry 4.0, and achieve sustainability goals.

Sustainability assessment and implementation must address supply chain goals, factors, and criteria to achieve performance and competitive advantage [17], [18]. The implementation of sustainability goals for the agroindustry potentially minimizes the negative impact of the uncertainty and dynamism of natural resource management on economic, social, and environmental impacts [19]. To attain sustainability goals, there is a need for current information on supply chain sustainability performance to assess and formulate activities for achieving a sustainable supply chain.

The implementation of sustainability in an agroindustry supply chain faces huge challenges, a dynamic environment, and uncertainty. One of the main challenges is to maximize profit, but it should simultaneously control the environment and social impact. Moreover, sustainability implementation must consider multidimensional perspectives and indicators, limitations of information for aggregating data, and multiple stakeholders to efficiently improve the supply chain's competitive advantage. Furthermore, a study by [19] mentioned that another important and ultimate challenge in the implementation of sustainability is to realize the current sustainability performance through an in-depth analysis and measurement of sustainability dimensions and indicators.

The challenge in acquiring data and information on sustainability performance assessment and implementation is consistent with another study [20], which found no appropriate indicators or frameworks to assess sustainability. This issue is becoming increasingly challenging for the agroindustry's supply chain, which has complex, imprecise, and uncertain variables. One study [21] found that the dimensions and indicators of sustainability have no standard formulation or measurement systems. Therefore, some researchers [22] suggested the design of a comprehensive sustainability assessment system and framework for Agroindustrial supply chains. To address this issue, an adaptive supply chain sustainability evaluation model must be designed to assess sustainability performance and develop an improvement strategy for uncertain and impression environment. An adaptive model for sustainability performance is designed to improve the previous model in sustainability evaluations, which is a qualitative assessment, has high potential in subjective assessment, and potentially increases the error in fulfilling the assessment of each indicator and less adaptability. Further, a fuzzy approach with multi-criteria assessment for supply chain sustainability can be designed, which will help in dealing with the uncertainty, ambiguity, and vague assessment found in supply chains and sustainability problems.

An adaptive supply chain sustainability assessment model using multi-criteria for the agroindustry can provide information on sustainability performance and recommend efficient methods for improvement. This model is designed to be adaptive in accommodating the data dynamism and uncertainty environment of supply chain sustainability indicators, as found in the real world. This study designs and applies the model to the sugarcane agroindustry in Indonesia, which plays a significant role in economic and social aspects, has a potential impact on the environment, and contributes to gross domestic products. Designing and implementing a sustainable supply chain for the sugarcane agroindustry is important because it includes managing natural resources, involves many stakeholders and communities, and adversely affects the environment through business process activities.

The first stage in designing an adaptive multi-criteria supply chain sustainability assessment model is to determine the indicators and dimensions of the sustainability assessment. This study designs a model for the sugarcane agroindustry. The indicators and dimensions were adopted from field observations and a literature review, and were then validated by experts, as described in [23]. The developed supply chain sustainability assessment model must adapt uncertain variables and the dynamic values of variables, as found in the real world [24]. For data and system adaptability, we implemented a fuzzy logic approach, that is, a fuzzy inference system (FIS) and an adaptive fuzzy inference system (ANFIS), to evaluate supply chain sustainability. FIS and ANFIS perform well in processing uncertainty and imprecision variables, and quantitative and qualitative data of sustainability indicators in the supply chain and agriculture [25]–[28]. Fuzzy logic has also been recommended to adapt ambiguous and uncertain data, as found in SCM, and to deliver proper recommendations for maintaining supply chain sustainability [4].

Strategies need to be developed to improve supply chain sustainability. This study develops an improvement strategy by analyzing key indicators of sustainability dimensions. In this stage, the cosine amplitude method (CAM) is proposed to identify the key indicators of the sustainability dimension, as proposed in Ref. [29]. Subsequently, an improvement strategy was developed based on key indicator analysis and expert discussion.

The objective of this study was to design an adaptive fuzzy multi-criteria assessment model and formulate a strategy for improving supply chain sustainability. The novelty and contributions of this study are as follows. First, the indicators and dimensions for sustainability assessment in the sugarcane agroindustry supply chain with adaptive fuzzy-based modeling are presented. To the best of our knowledge, no studies thus far have provided a detailed value and benchmark for

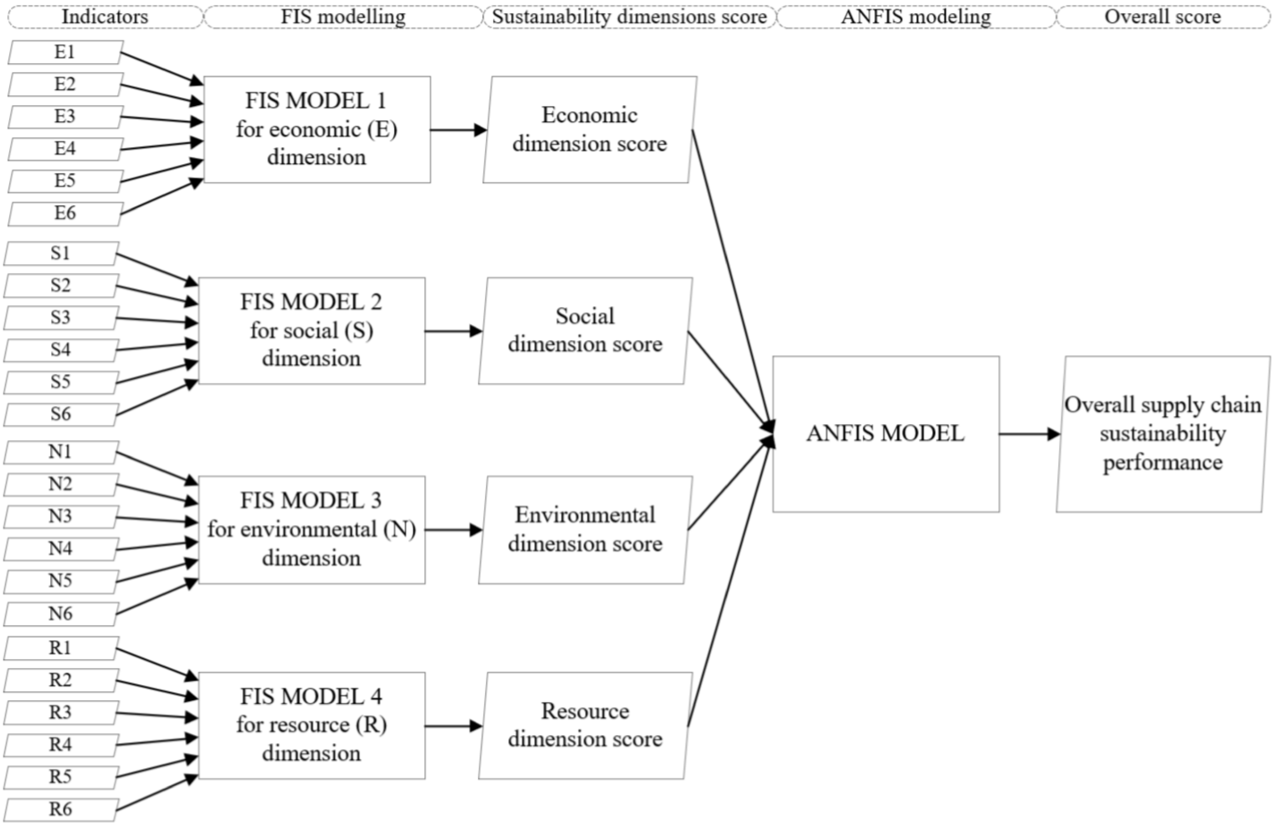

FIGURE 1. General research framework.

sustainability indicators and dimensions using qualitative and quantitative approaches. Second, considering the issues of ambiguity, uncertainty, and vagueness during the data acquisition stage, an adaptive model with multi-criteria sustainability assessment modeling was proposed. A complete stage and framework for model development applied to sustainability performance assessment and improvement of agroindustry supply chains was provided for practical application and contributions. Finally, this study contributes to sustainability improvement strategies in the sugarcane supply chain based on sustainability assessment results.

This paper is organized as follows: Section II describes the detailed process of model development; Section III presents the model testing and validation for the sugarcane agroindustry; and Section IV presents the conclusions and recommendations.

II. METHODOLOGY

A. RESEARCH FRAMEWORK

The research framework is illustrated in Figure 1. The framework is organized into three main parts: indicators, FIS modeling, and ANFIS modeling. The FIS was developed to assess the performance of sustainability dimensions, while ANFIS assessed the aggregate dimensions of overall supply chain sustainability performance.

The design of an adaptive sustainability multi-criteria assessment model requires dimensions and indicators with respect to the sugarcane supply chain configuration. To obtain indicator data in the sugarcane agroindustry and agriculture, which have many challenges [30], a special approach is required [31]. Data of indicators in sustainability must avoid a Boolean or categorical data type, and should provide a specific formulation to define sustainability performance. Therefore, in this case, FIS and ANFIS can manage data and infer solutions.

Specifically, the FIS environment was applied to accommodate the uncertainty and imprecision of indicator data in the sugarcane supply chain. The FIS model also accommodates qualitative and quantitative data from field observations. FIS modeling in a qualitative and quantitative data environment is proposed as one of the novelties of this study. FIS also enables the process of transforming the uncertainty and vagueness of a multi-criteria input into a crisp output for practical decision-making.

B. RESEARCH STAGES

Figure 2 illustrates the research stage. The study begins with the identification of the supply chain mechanism to analyze the business processes and stakeholders involved in the system. The sugarcane agroindustry in East Java, Indonesia, as the central producer of sugar [32], was selected as the case

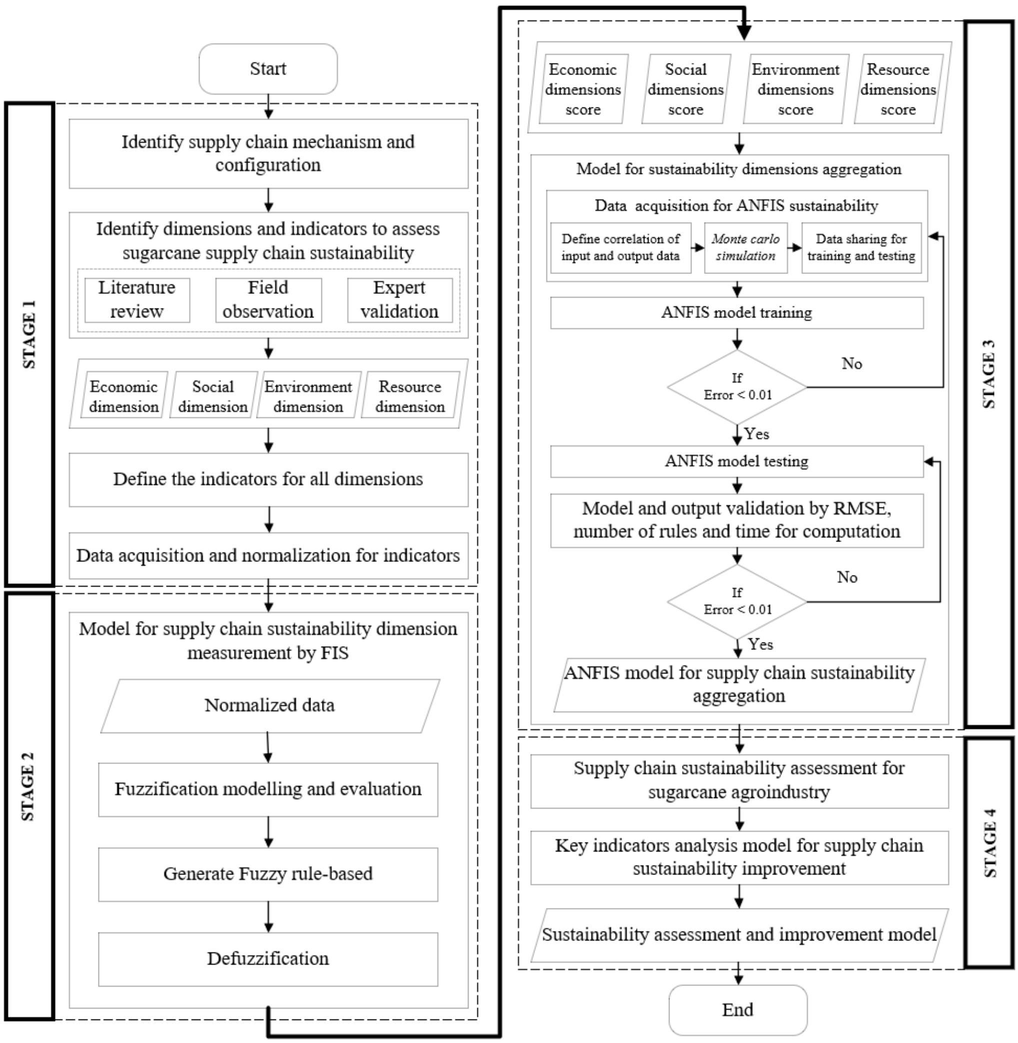

FIGURE 2. Research stages.

study. This study analyzes the phenomenon of the sugarcane agroindustry supply chain and sustainability to validate the sustainability assessment model using a fuzzy multicriteria approach. The research stages are as follows:

1) SUPPLY CHAIN IDENTIFICATION AND SUSTAINABILITY'S INDICATORS FORMULATION

In supply chain research, the first stage is to identify the supply configuration [33], [34]. In this case, supply chain identification is required to define the stakeholders involved in the model and to assist in constructing the dimensions and indicators. Formally, the supply chain identification stage analyzes the stakeholders, business process activities, and supply chain mechanisms to produce and deliver products to consumers.

Dimensions and indicators are required to assess current performance when designing a sustainability assessment model. These dimensions reflect the value of sustainability from many perspectives, while indicators describe the performance of the sustainability dimension for an organization [35]. Dimensions and indicators should reflect the objective of the study, such as the sugarcane agroindustry supply chain. With respect to Ref. [23], [36], [37], the dimensions and indicators in this study were defined through a literature review, expert, stakeholder, and practitioner validation, and field observation activities.

According to the literature, sustainability indicators should include the following considerations: they should be validated by experts and supply chain stakeholders [23], provide qualitative or quantitative data. and supported by data availability in the field [38], [39], whereas a sustainability dimension should be organized by at least six indicators [19]. Assessing the indicators using qualitative and quantitative approaches helps avoid subjective assessment and potential errors in managing indicator scoring found by the expert, as found in previous research [19]. In addition, a qualitative and quantitative approach to the indicator can track the performance value and easily adapt to other sectors.

Based on these considerations, this study defined 24 qualitative and quantitative indicators to describe the economic (E), social (S), environmental (N), and resource (R) sustainability dimensions. The economic, social, and environmental dimensions are triple bottom lines that have been theoretically and practically assigned to assess sustainability performance, as found in previous research [6], [17], [40]. Furthermore, this study also considers the resource dimension as it discusses the sugarcane agroindustry that encounters problems in resource allocation [41]–[44] and the high utilization of natural resources with low machine performance [45], [46], which is found to be the main problem in developing countries [38]. Considering that the resource dimension for sustainability assessment was applied in Ref. [47]–[49], to avoid any overlap between the dimensions in this study, the resource dimension is restricted to labor, raw material quality, and production machinery, which are the main issues in the sugarcane agroindustry. Six indicators for each dimension were validated by experts and sugarcane supply chain stakeholders (Table 1). Indicators were identified through a literature review and validated in the field by an expert through in-depth interviews. Experts contributed to validating each indicator based on real-world conditions. The identification and verification of the indicators along with the literature review are shown in upcoming Table 5.

2) FUZZY INFERENCE SYSTEM (FIS) MODELING FOR ASSESSMENT OF MULTI-CRITERIA SUSTAINABILITY DIMENSIONS

The fuzzy approach was first proposed in Ref. [50], and the FIS is part of the fuzzy approach for decision-making. To infer and provide a conclusion, the FIS converts the process of uncertainty and vague multi-criteria input into a crisp output for the decision maker. In inference processing, the FIS is organized by data input and fuzzification, generating rules, implication, aggregation, defuzzification, and output. This study applies the Mamdani inference system type because the model is simple, accommodates expert judgment, and is appropriate for supply chain sustainability, which involves a complex and comprehensive assessment [22], [51], [52]. The details of each FIS model stage for sustainability performance evaluation are explained below.

a: FUZZIFICATION AND NORMALIZATION OF MULTI-INDICATORS SCORE

The input and fuzzification sections of the FIS model represent indicator data (Table 1). All indicators were normalized and scaled into [0, 1] with five levels of linguistic values: very low (VL), low (L), moderate (M), high (H), and very high (VH) with respect to each indicator's target. Transforming the actual data of each indicator to normalize the value yields a different formula for qualitative and quantitative data. The normalization stage is required to prepare the data in different directions to adapt to the fuzzy system input and fuzzification [4], [52].

As qualitative indicators are collected by expert group assessment through a fuzzy scale, they need to be aggregated and normalized, which is referred to as fuzzy logic operations. The fuzzy expert assessments were aggregated by an ordered weighted average, as defined in Ref. [53]. The aggregated expert assessment was transformed into an interval value, as defined in Ref. [54]. Suppose that $\boldsymbol{X}$ (x_1, x_2, x_3) and $\boldsymbol{Y}$ (y_1, y_2, y_3) are triangular fuzzy numbers, and α is the confidence level. The fuzzy operations are described in Equations 1 and 2 with g and h as interval values. Quantitative indicators were collected using direct measurements according to the formula presented in Table 1. The normalized values of the indicators with the maximum (max) and minimum (min) targets were measured using Equations 3 and 4, respectively. Suppose that $N(I_i)$ is the normalized value of the indicator i (I_i). $T(I_i)$ represents the target of indicator i and the maximum *(max(i))* or minimum *(min(i))*. The indicator data were normalized to intervals of 0–1.

Fuzzification is a process that transforms actual data into fuzzy numbers using a specific membership function. Some fuzzy numbers include triangular fuzzy number (TFN), trapezoidal, and a mix of TFN-trapezoidal types. In this study, the decision to apply the fuzzification model of membership functions was made to refer to the error test of the model and compare it with the MDS and linear calculation results. The errors were compared using the root-mean-square error (RMSE).

$$X_a = [(x_2 - x_1)\,a + x_1, -(x_3 - x_2)\,a + x_3] = [g_1, g_2] \tag{1}$$

$$Y_a = [(y_2 - y_1)\,a + y_1, -(y_3 - y_2)\,a + y_3] = [h_1, h_2] \tag{2}$$

$$N(I_i) = \begin{cases} \dfrac{I_i - min(i)}{T(I_i) - min(i)}; & if\ I_i \le T(I_i) \\ 1; & if\ I_i \ge T(I_i) \end{cases} \tag{3}$$

$$N(I_i) = \begin{cases} 1; & if\ I_i \le T(I_i) \\ \frac{max(i) - I_i}{max(i) - T(I_i)}; & if\ I_i \ge T(I_i) \end{cases} \tag{4}$$

b: FUZZY RULES GENERATION

The FIS rules are required to assess the performance of sustainability dimensions using a combination of six indicators. Table 1 presents six indicators for each dimension. The number of rules for each dimension is determined by the number of linguistic levels in the membership function (N_j) for the *jth* variable input, as defined in Equation 5. Because there are five linguistic levels for each indicator and six indicators for each dimension, 15,625 rules must be prepared for each FIS model in the economic, social, environmental, and resource dimensions.

$$Number\ of\ fuzzy\ rules = \prod_{i=1}^{n} N_j \tag{5}$$

The FIS rule is organized into antecedent and consequent parts. The antecedent part consisted of the input variables of

TABLE 1. Indicators for supply chain sustainability in sugarcane agroindustry.

No	Dimension	Indicators	Data type	Formula
1	Economic (E)	Supply chain risk (E1)	Qualitative	Expert assessment aggregation using Fuzzy-House of Risk
2		Production loss (E2)	Quantitative	$FIS(E2) = f(Blotong, Bagasses, Molasses, Yield\ loss)$
3		Profit allocation (E3) (%)	Quantitative	$E3 = Profit\ of\ stakeholder\ i - profit\ stakeholder\ j;\ i, j \in N(supply\ chain\ stakeholder)$
4		Farmer reference price (E4) (%)	Quantitative	$E4 = \frac{current\ farmer\ price - reference\ price}{100\%}$
5		Agility performance (E5) (%)	Quantitative	$E5 = \left(\frac{current\ number\ of\ product\ delivery - previous\ number\ of\ product\ derlivery}{previous\ number\ of\ product\ derlivery}\right) \times 100\%$
6		Return on Investment (E6) (%)	Quantitative	$E6 = \left(\frac{Total\ sales - investment}{investment}\right) \times 100\%$
7	Social (S)	Institutional support (S1)	Qualitative	Level of institutional support in improving supply chain effectivity and efficiency, which are assessed by expert
8		Supply chain infrastructures (S2)	Qualitative	Level of infrastructure availability and condition as road, electricity, and transportation mode to assist the supply chain activities, assessed by the expert group
9		Corporate Social Responsibility (S3)	Qualitative	Level of CSR impact for the communities around agroindustry, which are assessed by stakeholder and expert
10		Waste complaints (S4)	Qualitative	Number of any complaint from the around communities about the liquid waste of the agroindustry
11		Local labor presentation (S5) (%)	Quantitative	$S5 = \left(\frac{Number\ of\ local\ labor}{Number\ of\ total\ labor}\right) \times 100\%$
12		*Stakeholder* partnership (S6) (%)	Quantitative	$S6 = \left(\frac{Deviation\ of\ the\ number\ of\ partnership\ sugarcane\ in\ this\ and\ last\ period}{Number\ of\ partnersip\ sugarcane\ in\ the\ last\ period}\right) \times 100\%$
13	Environmental (N)	Odor and dust disruption to community (N1)	Qualitative	Level of Odor and dust disruption to community around agroindustry, which are assessed by stakeholder and expert
14		CO_2 emissions (tCO_2/Ton Product) (N2)	Quantitative	$N2 = \frac{Number\ of\ electricity\ used\ (MWh) \times 0.485\ {}^{tCO_2}/_{MWh}}{Number\ of\ product\ (Ton)}$
15		Noise level (N3)	Quantitative	FIS N3 = *f(Workplace noise (dB), Open space noise (dB))*
16		Water quality (N4)	Quantitative	FIS N4 = *f(Total Suspended Solid, Biological Oxygen Demand, Chemical Oxygen Demand, Sulfide)*
17		Ambient Air quality (N5)	Quantitative	FIS N5 = *f(Sulfur Dioxide, Carbon monoxide, Nitrogen Dioxide, Dust)*
18		Solid waste (Solid / product) (N6)	Quantitative	$N6 = \frac{Blotong(kg) \times 0.76\% \times 0.005\ {}^{kgNOx}/_{kgN} \times 0.7kgSO_{2-eq}}{Number\ of\ total\ product(kg)}$
19	Resource (R)	Accessibility for labor (R1)	Qualitative	Level of accessibility for labor resource in agroindustry with appropriate number and competency
20		Sugarcane field conversion (R2) (%)	Quantitative	$R2 = \left(\frac{sugarcane\ land\ area\ in\ previous\ period - sugarcane\ land\ area\ in\ current\ period}{sugarcane\ land\ area\ in\ current\ period}\right) \times 100\%$
21		Labor competitive performance (R3)	Quantitative	FIS R3 = *f(labor productivity(%), labor training(%))*
22		Raw material quality (R4)	Quantitative	FIS R4 = *f(sugarcane productivity (Ton/Ha), sugar content (%)*
23		*Overall recovery* (R5) (%)	Quantitative	FIS R5 = *f(boiling house recovery, mill extraction)*
24		Adequacy of raw material (R6) (%)	Quantitative	Level of raw material availability with respect to mill's total capacity

the FIS dimension model. In this study, each input variable is related to the operator "and." This consequence reflects the dimensional performance, which, in the Mamdani model, is represented by a linguistic label. The linguistic label of the dimension's performance was organized into five levels: very low, low, moderate, high, and very high. The reflections of the variable input relations were validated by experts to determine the appropriate consequence part of the fuzzy rule. Moreover, because the initiation rule generation is validated by experts, this study applies a method to generate rules, as proposed in Ref. [55].

Supply chain sustainability is determined by four dimensions: economic (E), social (S), environmental (N), and resource (R). The fuzzy rules are defined and developed as follows:

- The linguistic scales of the fuzzy input were transformed into integers. Five levels of fuzzy input, namely, very low, low, moderate, high, and very high, are transformed to 1, 2, 3, 4, and 5, respectively.
- The sustainability dimensions were represented by 15,625 rules. For example, for the fuzzy rule number 10,955 of economic dimensions, the antecedent part of the rule is *If (risk is high) and (production loss is very high) and (profit allocation is very high) and (reference price is moderate) and (agility performance is very low) and (return on investment is high); then, economic sustainability is high (1)*. The transformed value is defined as follows:

$$\text{Transformed value (TV) for rule No. } 10,955 = 4 + 5 + 5 + 3 + 1 + 4 = 22$$

The consequence is further defined based on the sum of TV.

- The output value of the antecedent parts for the dimensions is categorized into five classes according to the consequent linguistic levels. For instance, the economic dimensions show that the output values range from six to 30. Furthermore, the classification of the transformed output value to determine the consequent rule is as follows:

$$\text{Fuzzy set consequent part} = \begin{cases} VL; & if\ 6 \leq TV \leq 10 \\ L; & if\ 11 \leq TV \leq 15 \\ M; & if\ 16 \leq TV \leq 20 \\ H; & if\ 21 \leq TV \leq 25 \\ VH; & if\ 26 \leq TV \leq 30 \end{cases}$$

c: DEFUZZIFICATION AND FIS MODEL COMPARISON

The FIS model for assessing the sustainability dimensions performance for this study applies an implication method "min" and aggregated by "max" function. Finally, defuzzification was applied to determine the output of the dimension performance. Defuzzification techniques include centroid, mean of maximum (MOM), largest of maximum (LOM), smallest of maximum (SOM), and bisector. To select the technique for use in the model, the lowest error in the model should be compared with the MDS and linear calculation results.

The MDS model for sustainability assessment was introduced in Ref. [56] to assess the sustainability of fisheries. MDS has been applied in many research areas; moreover, it is restricted to nominal or ordinal assessments. The model is based on the root mean square and Euclidean distance, which have been well defined in [5] and [10]. Furthermore, the linear calculation method is a simple model for comparing the FIS sustainability model assessment using equal weights for each dimension's indicators.

Suppose i_{jk} is indicator j of sustainability dimension k, and w_{jk} is the weight of indicator j of sustainability dimension k. As the weight is determined by the equal weight and each dimension is organized by six indicators, w_{jk} is equal to 1/6. The linear calculation model for comparison with the FIS sustainability model is expressed in Equation 6.

$$\text{Linear sustainability model} = \sum_{j,k} i_{j,k} \times w_{j,k} \tag{6}$$

Further, the decision to use the appropriate function and model in the FIS to assess supply chain sustainability was evaluated using the RMSE. Finally, Table 2 summarizes the function and model applied to generate the FIS model for evaluating sustainability dimension performance.

3) ANFIS MODELING FOR DETERMINING OVERALL SUPPLY CHAIN SUSTAINABILITY PERFORMANCE

ANFIS was first proposed in [57] as a hybrid model of an artificial neural network (ANN) and FIS. ANFIS helps adaptively design the membership functions (MFs) of the input variables based on the training process. In designing ANFIS for aggregating supply chain sustainability performance, some aspects must be considered, such as the initiation model (grid partition or subtractive clustering), number of MFs of input variables, number of data training pairs, epochs, and model error tolerance.

TABLE 2. Parameters for generating FIS model.

No	Parameters	Function / Model
1	Fuzzy inference model	Mamdani
2	Membership function	Triangular Fuzzy Number (TFN)/ Trapezoidal/mix
3	Operator	AND
4	Implication function	Min
5	Aggregation function	Max
6	Defuzzification function	Centroid/SOM/MOM/LOM/Bisector
7	Model validation test	RMSE with MDS and linear calculation

TABLE 3. Parameters to design the ANFIS model.

Parameters	Description	Source
MF	Gaussian	[27]
Initiation models	Grid partition and Subtractive Clustering	Evaluated by RMSE, MAPE, MAE [28]
Learning model	Hybrid	[57]
Number of Epochs	200	
Error tolerance	0	[60]

First, there are two initiations of membership function (MF) modeling in ANFIS: grid partition and subtractive clustering. For the grid partition, all variables were organized by five linguistic MFs, ranging from very low to very high. For subtractive clustering, MFs are developed automatically based on data input relative to the parameters of the subtractive cluster technique [58]. The performance of the two initiations was evaluated to find a suitable model with the lowest error and computation time for aggregating supply chain sustainability.

This study applied a Gaussian membership function model because it appropriately describes the data distribution of a real-world problem [59] and has the lowest error on average compared with training and testing data [27]. For the training data model, a hybrid learning model was applied as a combination of gradient descent and least-squares estimation to identify the linear parameters of the adaptive network [57]. To train the model, 200 epochs were set with zero-error tolerance. The error tolerance number is given in Ref. [60] that a fit ANFIS model must have an error lower than 0.01. The parameters used to set and develop the ANFIS model for the aggregated supply chain sustainability of the sugarcane agroindustry are listed in Table 3.

TABLE 4. Expertise area/institutions involved in the research.

No	Areas of expertise /institutions
1	Researcher in sugarcane plantation and cultivation
2	Academician in sugar factory and engineering
4	Academician and researcher of sugarcane plantation and sugar agroindustry
5	Researcher in sugarcane and sugar business management
6	Researcher in sugarcane plantation and business management
7	Experienced practitioner in sugarcane plantation and cultivation
8	Experienced practitioner in sugar mill and sugar agroindustry
9	Experienced practitioner in sugarcane and sugar quality management
10	Government and regulator in food industry

4) KEY PERFORMANCE ANALYSIS AND IMPROVEMENT STRATEGY FORMULATION USING COSINE AMPLITUDE METHOD

To improve supply chain sustainability, key indicators must be determined. In this stage, sustainability is assessed, and key indicators are identified by developing an improvement strategy. The cosine amplitude method (CAM) proposed in Ref. [29] was applied to analyze the key sustainability indicators. The CAM is proposed, as it performs well in synthesizing the fuzzy indicators applied in this study.

The key indicators analysis stage using CAM is described as follows:

1. CAM finds similarities between indicators i and $j(r_{ij})$. Indicators i and j have n datasets with m linguistic levels of fuzzy MF. The similarity between indicators i and j is determined using Equation 7:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik}x_{jk}}{\sqrt{\left(\sum_{k=1}^{m} x_{ik}^2\right)\left(\sum_{k=1}^{m} x_{jk}^2\right)}}; \quad i;\ j = 1, 2, \ldots, n \tag{7}$$

2. Key indicator analysis using six indicators (n) of sustainability dimensions and five MF (m)
3. The similarity values of the indicators were organized as pair-way comparisons to determine each indicator score.
4. The lowest score is defined as the key indicator for improving future supply chain sustainability performance.

Improvement strategies were developed through expert group discussion. The key indicators were analyzed, and an improvement agenda was found to maintain supply chain sustainability.

C. DATA COLLECTION

Assessing supply chain sustainability in the sugarcane agroindustry requires a certain definition of each sustainability indicator. As mentioned earlier, 24 indicators with four sustainability dimensions were defined and classified as qualitative and quantitative data needs. Qualitative and quantitative data were also collected.

The quantitative data of sustainability indicators were collected by analyzing related documents, studying previous research, and conducting in-depth interviews. The data were analyzed using a specific formula to determine the performance of each indicator (Table 1).

Qualitative data were collected through in-depth interviews, field observations, expert group opinions, and assessments. The expert personnel group consisted of professionals with various perspectives, institutions, business actors, researchers, and academicians in the sugarcane supply chain and sustainability field. This study involved ten experts in the field of the research objective, and the areas of expertise are presented in Table 4.

As a limitation of the actual data availability to build the model, this study generated 1,000 datasets using the Monte Carlo method with probabilistic distributions to develop the ANFIS model. This methodology was referred to in Ref. [56]–[58], proving that the data and model are valid. As mentioned by Ref. [64], 70% of the dataset was required for training, and the rest for testing. Therefore, 650 datasets were prepared as the training dataset and the rest as the testing dataset.

To generate the data, suppose that v_{out} is the sustainability value and the expected value of the ANFIS model; v_i as input data classified by economic, social, environmental, and resource dimension values and are generated by Monte Carlo simulation; and p_i is the probabilistic value of v_i with respect to Ref. [48]. The Monte Carlo simulation with a probabilistic distribution to generate data for developing the ANFIS model is explained in Equations 8–11.

$$v_{out} = \sum_{i=1}^{n} v_i \times p_i \tag{8}$$

$$v_{out} \leq 100 \tag{9}$$

$$v_i = [1, 100] \tag{10}$$

$$\sum_{i=1}^{n} v_i = 1 \tag{11}$$

D. MODEL VERIFICATION AND VALIDATION

The model verification and validation of this study are presented in Ref. [65]. The verification stage ensured that the formula and model were correct. At this stage, it is ensured that the formulation of the sustainability indicators in the FIS model is consistent with the current model and supported by the literature review. For the FIS and ANFIS models, verification was ensured by the lowest error of the model compared with real-world conditions. Validation is defined as ensuring that the model satisfies the system requirements and captures the current real-world conditions. In this stage, validation is performed by face validity, which requires expert knowledge to assess the model and illustrate the current condition of the real world.

A conceptual validation of the model is realized by ensuring that the sustainability indicator formula is correct, according to the literature review. As mentioned earlier, there are

24 indicators of the four sustainability dimensions used to assess supply chain sustainability performance. All sustainability indicators were determined through field surveys, expert opinions, and literature review. The proof of the verification of the sustainability indicator based on the literature review is presented in Table 5.

Furthermore, the performance of FIS and ANFIS modeling should be evaluated to ensure that the models are verified. The FIS model was evaluated using RMSE. As these parameters need the actual value, the results of the FIS sustainability assessment model were compared with those of the MDS and linear calculation models, as defined in the previous subsections.

The ANFIS model was also evaluated using parameters such as the RMSE, mean square error (MAPE), mean absolute error (MAE), computation time to generate rules, number of MFs and rules, training, and testing error.

Suppose that x_i is the targeted and expected value, y_i represents the observed value of the model, n is the number of the data; then, RMSE, MAPE, and MAE are explained in Equations 12–14. The number of MFs, computation time, training, and testing errors were obtained in the model development phase.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)}{n}} \quad (12)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{n} \left(\frac{|x_i - y_i|}{y_i} \times 100 \right) \quad (13)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |x_i - y_i| \quad (14)$$

III. RESULT AND DISCUSSION

A. SUPPLY CHAIN CONFIGURATION AND SUSTAINABILITY INDICATORS

The supply chain of the sugarcane agroindustry involves both primary and secondary stakeholders [66]. Secondary stakeholders assist primary stakeholders in ensuring the proper operation of the supply chain's business process. In Indonesia's sugarcane supply chain, secondary stakeholders include cooperative organizations and marketing offices. Moreover, this study considers primary stakeholders such as farmers, sugar mills, and distributors, who are responsible for the supply chain business, utilize natural resources directly, and impact the environment and society. Farmers provide raw materials for sugarcane processing in sugar mills Distributors are responsible for allocating consumed sugar to retailers and consumers. The sugarcane agro-industrial supply chain is illustrated in Figure 3.

Supply chain sustainability is determined by four dimensions: economic (E), social (S), environmental (N), and resource (R). Based on a literature review, field observations, and expert validation, 24 dimensions were selected to assess the supply chain sustainability of the sugarcane agroindustry. The dimensions were validated through expert discussions and literature review (Table 5).

TABLE 5. Sustainability indicators verification through literature review.

No	Indicators	Source
1	Supply chain risk (E1)	[84], [85]
2	Production loss (E2)	[86]
4	Profit allocation (%) (E3)	[66], [87]
5	Farmer reference price (%) (E4)	[37]
6	Agility performance (%) (E5)	[72]
7	Return on Investment (%) (E6)	[72]
8	Institutional support (S1)	[86], [88], [89]
9	Supply chain infrastructures (S2)	[90], [91]
10	Corporate Social Responsibility (S3)	[92]
11	Waste complaints (S4)	[93]
12	Local labor presentation (%)(S5)	[17], [85]
13	*Stakeholder* partnership (%)(S6)	[48], [71]
14	Odor and dust disruption to community (N1)	Interview and field observation
15	CO_2 emissions by electrical used [a] (tCO_2/Ton Product) (N2)	[76], [94], [95], [96]
16	Noise level (N3)	Indonesian government Regulation
17	Water quality (N4)	[97], [98]
18	Ambient air quality (N5)	[97]; Indonesian government regulation
19	Solid waste (N6)	[96]
20	Accessibility for labor (R1)	[41]
21	Sugarcane field conversion (%) (R2)	[37]
22	Labor competitive performance (R3)	[17], [98]
23	Raw material quality (R4)	[80], [81]
24	Overall recovery (%) (R5)	[45], [81]

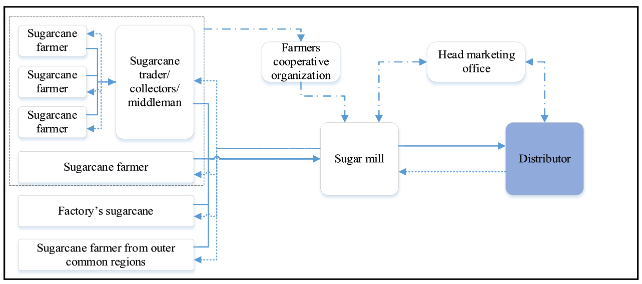

FIGURE 3. Sugarcane supply chain configuration.

The indicators in this study are related only to primary supply chain stakeholders, which were also applied in Ref. [22] and [63], who determined the overall value of supply chain sustainability performance. The indicators, minimum, maximum, and target values for assessing the supply chain sustainability of the sugarcane agroindustry are listed in Table 6. Indicators with linguistic labels were qualitative indicators, and the rest were quantitative indicators.

The proposed model was designed using qualitative and quantitative data as recommended in Ref. [67]. Qualitative data were collected through expert judgments of five fuzzy linguistic levels, whereas quantitative data were obtained through interviews, observations, and measurements.

B. SUPPLY CHAIN SUSTAINABILITY DIMENSION PERFORMANCE

The FIS model is applied to determine the performance of the sustainability dimensions, which are organized by six indicators. FIS models accommodate the uncertainty,

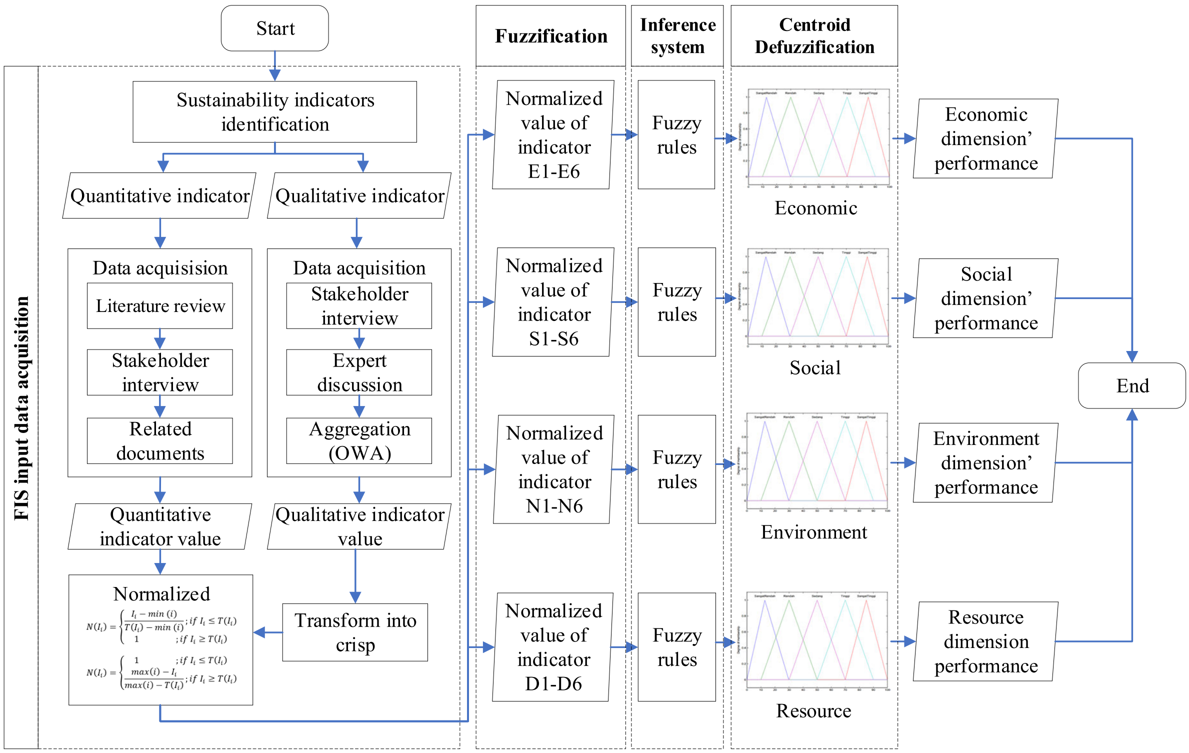

FIGURE 4. The framework for sustainability dimensions assessment using FIS.

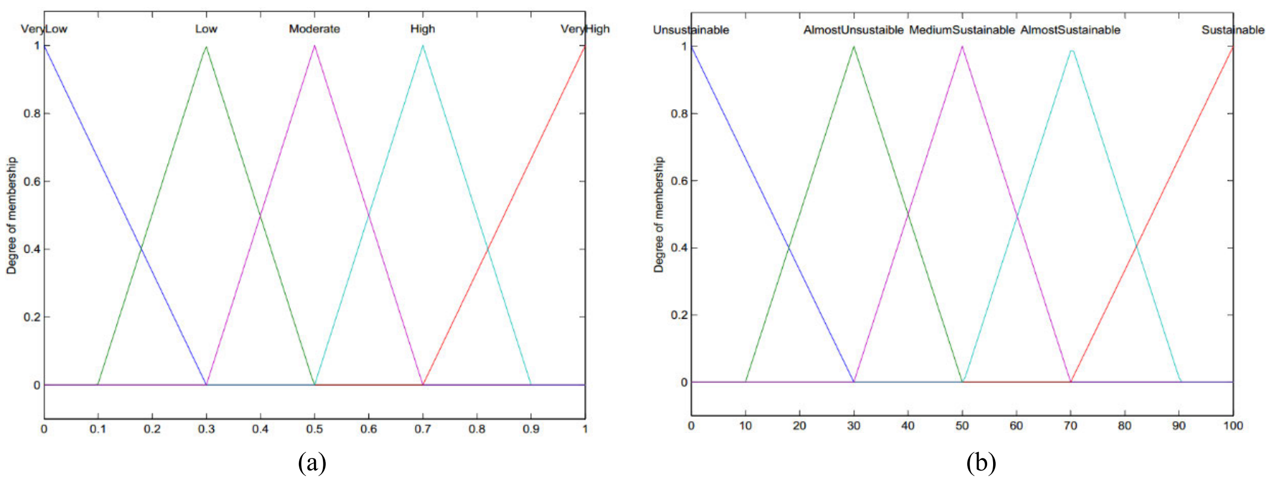

FIGURE 5. The membership function of (a) fuzzy input and (b) output for sustainability dimension performance.

handling qualitative data from expert judgment and the quantitative data to process into a robust final score. Qualitative and quantitative data acquisitions are considered limitations and uncertain real-world conditions in agricultural business processes. As mentioned earlier, the Mamdani FIS inference model was implemented with five-level TFN MFs, six indicator inputs, and one sustainability dimension output. The completed framework of sustainability dimension evaluation is shown in Figure 4.

The TFN membership function was chosen to model the sustainability assessment because it has a lower error than the other membership function types. To evaluate the error and prove that the TFN model is suitable, the RMSE was organized and compared with the MDS technique and linear calculation error. The results of the Mamdani and TFN model validation are presented in Table 7.

Four models were developed for the sustainability assessment of the economic, social, environmental, and resource dimensions using FIS. As there are six indicators for each dimension, 15,625 rules (5^6) must be generated to infer the sustainability performance of each dimension. The MF of the fuzzy input–output of the FIS model to determine the

TABLE 6. Dimension and indicators for assessing supply chain sustainability for sugarcane agroindustry.

No	Indicators	Min value	Max value	Target	Data actual	Normalized
1	Supply chain risk (E1)	Very low	Very high	Min	Moderate	0.491
2	Production loss (E2)					0.204
	a. Blotong (%)	0	2.6	Min	2.22	0.146
	b. Bagasse (%)	0	2	Min	1.59	0.205
	c. Molasses (%)	0	30	Min	29.67	0.011
	d. Yield loss by transportation (%)	0	0.64	Min	0.49	0.234
3	Profit allocation (%) (E3)	15	30	Min	26	0.267
4	Farmer reference price (%) (E4)	0	6.87	Min	1.36	0.953
5	Agility performance (%) (E5)	0	25	Max	23	0.920
6	Return on Investment (%) (E6)	5	50	Max	29.91	0.554
7	Institutional support (S1)	Very low	Very high	Max	Moderate	0.509
8	Supply chain infrastructures (S2)	Very bad	Very good	Max	Good	0.789
9	Corporate Social Responsibility (S3)	Very bad	Very good	Max	Moderate	0.509
10	Waste complaints (S4)	Very low	Very high	Min	Low	0.712
11	Local labor presentation (S5) (%)	0	100	Max	80.9	0.809
12	*Stakeholder* partnership (S6) (%)	0	15	Max	3.4	0.227
13	Odor and dust disruption to community (N1)	Very low	Very high	Min	High	0.211
14	CO_2 emissions by electrical used [a] (tCO_2/Ton Product) (N2)	0	0.236	Min	0.188	0.294
15	Noise level (N3)					0.495
	a. Work place noise (dB)	50	85	Min	64	0.600
	b. Open space noise (dB)	40	55	Min	48	0.467
16	Water quality (N4)					0.692
	a. Total of suspended solid (mg/L)	0	25	Min	4.00	0.840
	b. Biochemical Oxygen Demand (BOD_5) (mg/L)	0	60	Min	7.42	0.876
	c. Chemical Oxygen Demand (COD) (mg/L)	0	100	Min	43.39	0.566
	d. Sulfide (mg/L)	0	0.5	Min	0.02	0.960
17	Ambient Air quality (N5)					0.793
	a. Sulfur dioxide ($\mu g/Nm^3$) (Max Standard 365)	0	262	Min	6.8	0.974
	b. Carbon monoxide ($\mu g/Nm^3$)	0	10,000	Min	1495	0.851
	c. Nitrogen Dioxide ($\mu g/Nm^3$) (Max Standard 150)	0	92.5	Min	26.9	0.709
	d. Dust ($\mu g/Nm^3$) (Max Standard 230)	0	0.23	Min	0.078	0.700
18	Solid waste (solid/product) (N6)	0.0067	0.024	Min	0.012	0.694
19	Accessibility for labor (R1)	Very low	Very high	Max	Moderate	0.509
20	Sugarcane field conversion (%) (R2)	0	10	Min	8.16	0.184
21	Labor competitive performance (R3)					0.573
	a. Labor productivity (%)	50	100	Max	81.2	0.624
	b. Training hour (%)	0	67.5	Max	35	0.519
22	Raw material quality (R4)					0.478
	a. Sugarcane productivity (Ton/Ha)	55	88	Max	69	0.424
	b. Percent of sugar content of sugarcane(%)	6	10	Max	7.45	0.363
23	*Overall recovery* (%) (R5)	80	87.5	Max	82.50	0.333
24	Adequacy of raw material (%) (R6)	80	100	Max	90.01	0.505

sustainability performance of each dimension is shown in Figure 5.

In this study, the fuzzy rule related to the methodology proposed in Ref. [55]. The FIS framework for determining the performance of supply chain sustainability for each dimension is depicted in Figure 6, while the 3-D view of the rule surface is depicted in Figure 7. Some rule examples for each dimension generated by the FIS are as follows:

1. If (supply chain risk is moderate) and (production loss is high) and (profit allocation is very high) and (farmer reference price is low) and (agility is low) and (ROI is low), then (economic sustainability is high).
2. If (institutional support is moderate), (supply chain infrastructure is high), (CSR is very high), (waste complaints are high), (local labor presentation is moderate), and (stakeholder partnership is low), then (social sustainability is moderate).
3. If (Odor and dust disruption to community is moderate), (CO_2 emission by electricity used is high), (noise level is very high), (water quality is low), (ambient air quality is very high), and (suspended waste is moderate), then (environment dimension sustainability is high).
4. If (accessibility for labor is moderate), (sugarcane field conversion is high), (labor performance is very high), (raw material quality is high), (overall recovery is very high), and (adequacy of raw material is very high), then (resource dimension sustainability is moderate).

Defuzzification is the last part of the FIS model used to evaluate supply chain sustainability for each dimension and define the output model by processing the fuzzy input (indicator data). This model applies the centroid defuzzification function related to the lowest error. In this study, MOM, LOM, SOM, bisector, and centroid were examined. Defuzzification functions were evaluated using RSME related to the

TABLE 7. FIS-fuzzification model performance evaluation using RMSE.

Type of error test	TFN	Trapezoidal	Mix of TFN and trapezoidal
RMSE to MDS	4.084	4.147	5.854
RMSE to linear calculation	3.750	5.720	3.862

TABLE 8. Defuzzification model performance evaluation using RMSE.

Type of error test	MOM	Centroid	SOM	Bisector	LOM
RMSE to MDS	5.240	4.076	6.311	4.996	10.342
RMSE to linear calculation	5.132	3.743	6.030	4.606	4.606

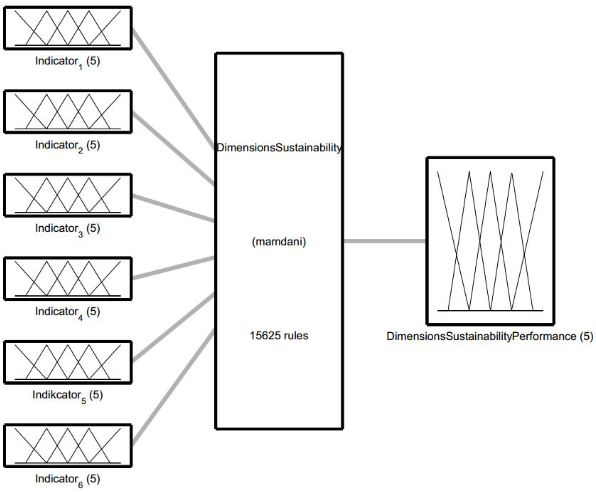

FIGURE 6. The framework of FIS model to assess sustainability dimension performance.

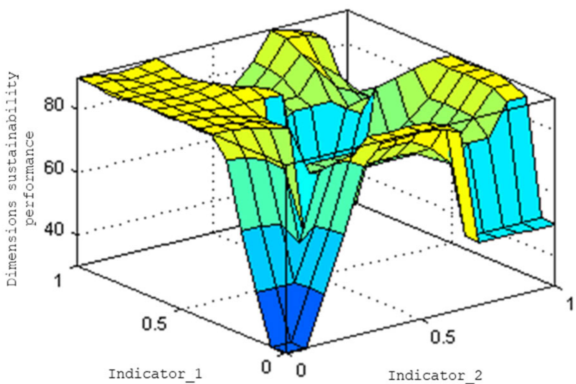

FIGURE 7. The surface of the fuzzy rules.

MDS and linear calculation results. The RMSE test results are presented in Table 8.

After several tests, the FIS model is used to evaluate the sustainability performance of the supply chain for each dimension. To determine the performance value of the sustainability dimensions, the normalized values of the indicators were set as the input of the FIS model. The economic, social, environmental, and resource performance dimensions were determined based on the data in Table 6 and

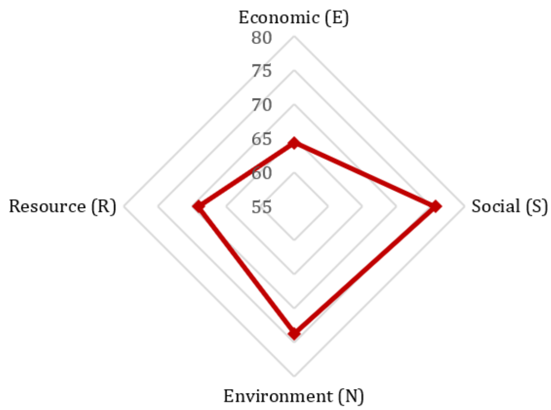

FIGURE 8. The sustainability dimensions performance.

the FIS model. The economic, social, environmental, and resource dimensions for the sugarcane agro-industry supply chain were 64.33, 75.69, 73.72, and 69.05, respectively. Figure 8 shows the supply chain sustainability dimensions performance for the sugarcane agroindustry.

Some indicators in each dimension threaten supply chain sustainability. These indicators must improve the overall sustainability performance of the supply chain. In terms of economic dimensions, fair profit allocation and supply chain risk lead to low performance, which affects economic sustainability. Fair profit allocation is an important issue in supply chain sustainability because it describes a fair and efficient business to improve stakeholder motivation and produce high-quality products [68]. Generally, the agro-industry supply chain faces an unfair profit distribution, especially for smallholder farmers [66], [69]. The data analysis shows that the supply chain profit distribution in the sugarcane supply chain is low and requires immediate improvement. Supply chain risk may affect the efficiency of the overall supply chain [70]; therefore, it should be minimized. Supply chain risk is related to uncertainty factors and causes supply chain loss [47], and experts agree that sugarcane supply chain risk is moderate.

In the social dimension, the partnership indicator is noteworthy. In the agroindustry and agribusiness, partnerships are required to improve coordination in providing resources and raw materials. Moreover, partnerships may improve stakeholders' bargaining position, especially smallholders [71]. The partnership performance of the supply chain is focused on the number of smallholder farmers joining the partnership scheme at the sugar mill to provide raw materials. The data show that the partnership only increases by 3%–4% a year, more than the supply chain operation reference (SCOR) recommends of 15% [72]. Another issue is that farmers' field areas for sugarcane production decreased year by year, as shown in Ref. [73] and [74], which affect supply chain partnership performance.

For the environmental dimension, three dimensions have low sustainability performance: odor and dust disruption to the community (N1), CO_2 emissions arising from electrical use (N2), and noise level (N3). Odor and dust disruption indicators were assessed through qualitative data by obtaining community responses to this disruption in daily life around sugar supply chain activities. The aggregated value of respondents shows that odor and dust disruption are high, although they should be low. CO_2 emissions were calculated as the total electricity required to produce a supply chain product. Excessive use of electricity may increase greenhouse gas effects and affect global warming [75]. The calculation of CO_2 emissions is referred to in a study [76], and the result is 0.188 ton-CO_2/ton product, whereas the benchmark value is adopted from [77] with 0.236 ton-CO_2/ ton product. As the target value of the indicator is minimized, the normalized formula shows that CO_2 exhibits low performance.

For the resource sustainability dimension, three indicators had low performance: sugarcane field conversion (R2), raw material quality (R4), and overall recovery (R6). The field-conversion issue has a significant impact on ensuring the availability of raw materials. This issue is supported by major infrastructure development, industrialization in agricultural areas, and a shift to other commodities that offer higher profits [78]. The number of field conversions was obtained from historical data compared with field availability for sugarcane farming in the current year, and the result was 8.16%. Further, this result is very high, referring to the benchmark at 10%, and is associated with a study by Ref. [79].

The raw material quality indicator is obtained using the FIS technique with sugarcane productivity and sugar content as input variables, and represents the main factors that ensure agroindustry performance [80]. The analysis showed that the sugarcane productivity performance after normalization was 0.424, whereas the sugar content was 0.363. This value affected the raw material quality performance using an FIS of 0.478, which indicates a low performance. The productivity and sugar content of sugarcane must be improved to support the production of sugar for domestic demand [44]. Additionally, the overall recovery indicator, which reflects machinery performance in transforming sugarcane to sugar as the main product of the sugarcane supply chain, needs to be improved. Data analysis showed that the overall recovery was 82.5%, while the international benchmark was 87.5% [45], [81]. Therefore, the overall recovery of Indonesian sugar mills is below the world standard.

C. THE ANFIS MODEL FOR AGGREGATING SUPPLY CHAIN SUSTANABIILTY

1) ANFIS MODEL DEVELOPMENT

The previous stage showed the performance of each sustainability dimension of sugarcane supply chains; therefore, it requires an aggregated value to reflect the overall supply chain sustainability performance. The ANFIS is a supervised model proposed in Ref. [57] as a hybrid model of an ANN and FIS. As ANFIS is a supervised model, the implementation of the aggregation of supply chain sustainability performance requires a dataset for training and testing the model. A dataset was prepared and organized using four inputs of economic, social, environmental, and resource, and one output of sustainability performance at intervals of 1 to 100 related to sustainability value, as classified by Ref. [82].

This study designs ANFIS with subtractive clustering and a grid partition initiation model to find the best-fit model to determine supply chain sustainability performance. The evaluation of each initiation model was based on the computation time, number of rules, and RMSE. For the grid partition model, an ANFIS model was used to aggregate supply chain sustainability organized by a Gaussian model with five MF levels. As it is decomposed into four input variables of sustainability dimension performance, it generates 15,625 fuzzy rules to generate one output as the overall supply chain sustainability performance. The interval of the five levels of MF is distributed fairly with respect to the dataset for training with the grid partition technique.

For the subtractive clustering initiation model, the subtractive cluster should be set to generate rules. This study sets the range of influence (0.5), squash factor (1.25), acceptance ratio (0.5), and reject ratio (0.15) to produce rules for generating the ANFIS model to aggregate the supply chain sustainability performance. Furthermore, model testing is required to ensure a fit model as a further phase of model training. In this phase, 350 datasets were tested, and the errors of each grid partition and subtractive clustering error were defined.

2) PERFORMANCE EVALUATION OF THE ANFIS MODEL

The ANFIS subtractive clustering and ANFIS with grid partition must be evaluated to find which model performs better and simulates the sustainability performance based on the sustainability dimension input. The evaluation of this model considers training and testing errors, computation time, number of generated fuzzy rules, RMSE, MAPE, and MAE. Table 9 presents an evaluation of the ANFIS model.

First, regarding computation time, ANFIS with the grid partition model required more time to develop than the subtractive model. For the topology, the grid partition model was developed using four inputs of sustainability dimensions with five MFs, while the subtractive clustering model was developed using five inputs with 26 MFs. The training data process shows that ANFIS with the subtractive clustering model generates 26 rules to evaluate sustainability performance, which is better than the grid partition's number of rules. ANFIS

TABLE 9. ANFIS model performance evaluation.

Parameters and ANFIS info	ANFIS model with Grid Partition	ANFIS model with Subtractive clustering
Computation time	24 hours	2.50 minutes
Type of MFs		
-Input	Gaussian	Gaussian
-Output	Linear	Linear
Number of MFs		
-Input	5,5,5,5	26,26,26,26
-Epoch	200	200
Learning method	Hybrid	Hybrid
Number of Fuzzy rules	625	26
Training error	3.1×10^{-5}	1.3×10^{-7}
Testing error	2.04	1.7×10^{-7}
RMSE	0.10	3.39×10^{-8}
MAPE	3.27	9.67×10^{-7}
MAE	1.19	1.94×10^{-7}

training is a meaningful stage in developing a model and finding a set of parameters with the lowest error. The data training for the ANFIS model with grid partition shows an error of 3.1×10^{-5}, whereas subtractive clustering with 1.3×10^{-7}. The training errors of both models fulfilled the error condition of 0.01 [60]. Moreover, subtractive clustering requires less time to generate a model with 2.50 minutes, while grid partition must deal with 24 h for each 200 epochs with 1,000 datasets.

The testing shows that a model with grid partition achieved 2.04 error, while that with subtractive clustering achieved only 1.7×10^{-7}. The ANFIS model with grid partition and subtractive clustering was also tested using the RMSE, MAPE, and MAE.

The RMSE, MAPE, and MAE parameters for the ANFIS performance evaluation showed that the ANFIS model with subtractive clustering performed better than the ANFIS with the grid partition model. The lowest RMSE, MAPE, and MAE scores confirmed that the model is appropriate for real-world conditions. Overall, based on the evaluation parameters, ANFIS with a subtractive clustering model had a better fit to accommodate sustainability supply chain aggregation.

3) ANFIS TOPOLOGY AND SIMULATIONS

The important aspects of ANFIS modeling are the MF and ANFIS topologies. The MFs of ANFIS with grid partition and subtractive clustering models after the training phase are shown in Figure 9.

After the training phase, the ANFIS shows a Gaussian membership function, which is also defined in the initiation model. The MF scales changed dynamically at every linguistic level, indicating that the model accurately represented the training data. The classification model shows that data training plays an important role in organizing the MF to predict output. Therefore, data training must be validated prior to the model training phase. This study applies the Monte Carlo method with probabilistic distribution for data acquisition, and studies have also proven that the approach is valid for the data training acquisition phase [61], [62], [83]. Moreover, with the ANFIS model evaluation mentioned earlier, the ANFIS model with subtractive clustering was found to be the fittest model to aggregate the overall supply chain sustainability performance, as proposed. Subsequently, ANFIS topology with subtractive clustering was explored.

ANFIS with subtractive clustering model initiation succeeded in designing four inputs of sustainability dimensions, 26 clusters and fuzzy rules, and one output of aggregated supply chain sustainability performance. The architecture of the ANFIS with a subtractive clustering model after testing and training is shown in Figure 10. The rule surface of the model is required to examine the relationships between the dimensions to define sustainability performance. The rule surface, which is generated from the ANFIS model with subtractive clustering initiation, is important for predicting and proposing the performance of machine learning to assess supply chain sustainability.

As 26 rules have been designed by the ANFIS model for an adaptive evaluation model, a sugar agroindustry practitioner can explore the current performance of supply chain sustainability and define activities for improvement. The 3D rule surface of the ANFIS model, organized by economic, social, environmental, and resource dimensions, is depicted in Figure 11.

Finally, the ANFIS model with subtractive clustering is implemented to infer the aggregated value of supply chain sustainability performance. This study validated the performance of the sustainability dimensions using the ANFIS model to perform the aggregated supply chain performance. The validation results show that the aggregated performance of supply chain sustainability for the sugarcane agroindustry is 68.58, according to Ref. [82], and is practically sustainable. The simulation of the supply chain sustainability performance for the sugarcane agroindustry using an adaptive model of ANFIS is depicted in Figure 12.

A computerized model was used to verify the model accuracy. The FIS model verification results are presented in Tables 7 and 8. The verification results show that the FIS model, which applies the Mamdani, TFN MF, and centroid defuzzification models, has the lowest error compared to the MDS and linear models. This model also fires well to define the sustainability dimensions of the sugarcane agroindustry. The ANFIS model verification to define the overall sustainability performance was verified using error values. The ANFIS model with subtractive clustering showed the lowest error, and it was accepted as the verified model.

Operational validation was performed using face validity. In this scheme, the model is tested and validated by an expert to ensure that it describes the real-world condition and fulfills the system requirements, which were agreed upon by the expert group. Currently, the sugarcane supply chain agroindustry faces sustainability and productivity problems that are affected by many indicators.

D. KEY INDICATORS FOR SUPPLY CHAIN SUSTAINABILITY IMPROVEMENT

Using the CAM approach, the key indicators to improve the sustainability performance of the sugarcane agroindustry

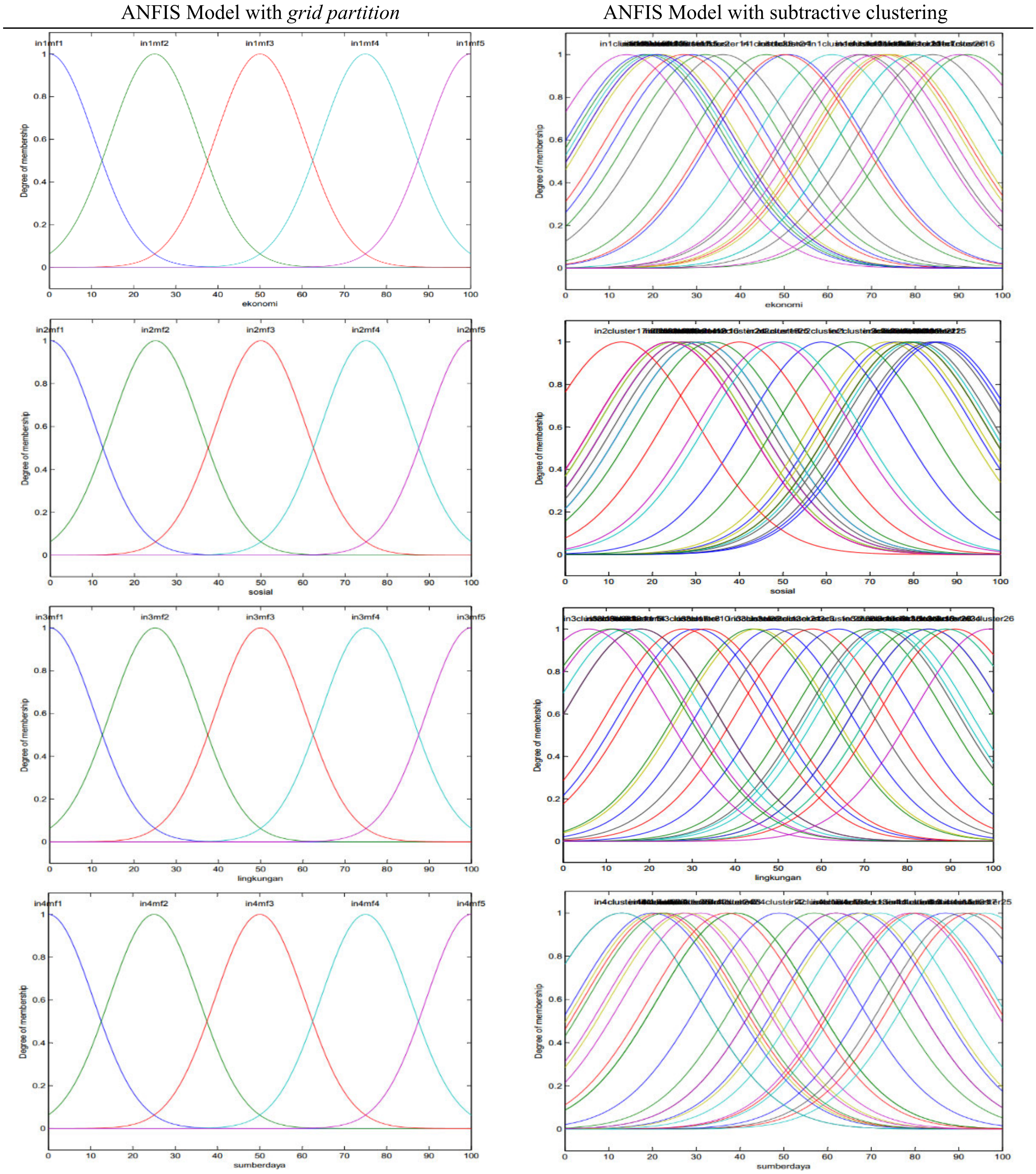

FIGURE 9. **After training membership function for ANFIS model.**

were revealed. The key indicators were examined for sustainability dimensions, including economic, social, environmental, and resource. The CAM indicates that indicators with low scores should be improved to maintain sustainability.

For the economic dimensions, the key indicators for improving supply chain sustainability for the sugarcane agroindustry are agility performance (E5), supply chain risk (E1), and profit allocation (E3). The key indicators for social dimensions are institutional support (S1), corporate social responsibility (CSR) (S3), and stakeholder partnership (S6).

The key indicators for the environmental dimensions were ambient air quality (N5), noise level (N3), and solid waste (solid/product) (N6). Finally, the resource dimension should focus on the following indicators: sugarcane field conversion (R2), labor competitive performance (R3), and overall recovery (R5).

Further, improvement strategies were developed based on key indicators. A panel discussion with an expert group was conducted to develop the strategy. Table 10 shows the detailed strategy improvements for every key indicator.

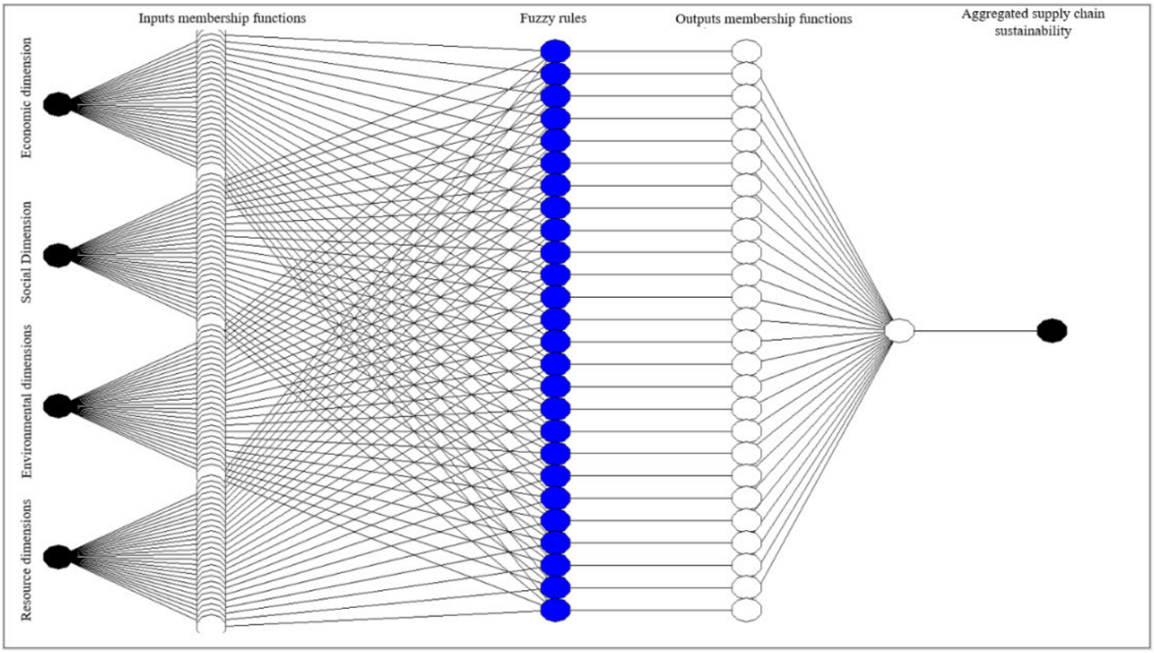

FIGURE 10. The architecture of ANFIS model for aggregating supply chain sustainability performance.

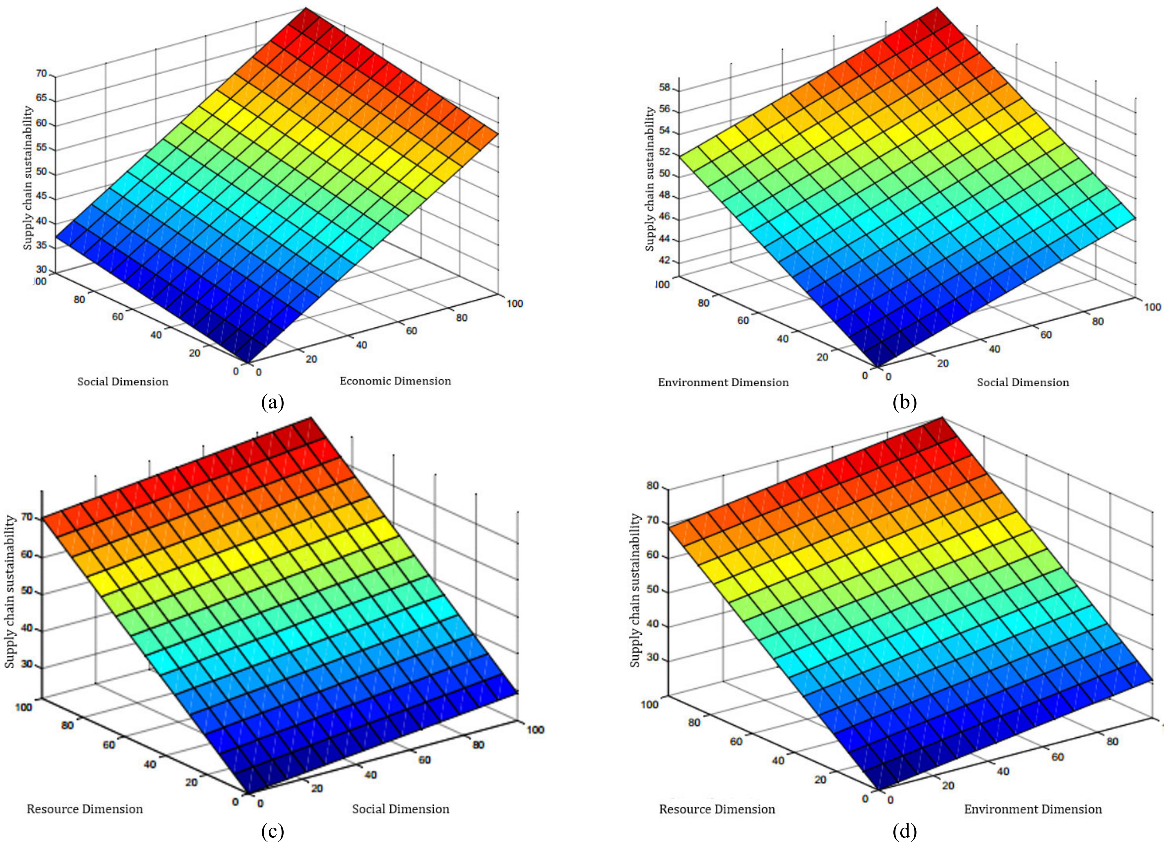

FIGURE 11. Rule surface of the adaptive model for sugarcane agroindustry supply chain sustainability assessment for (a) social and economic dimension, (b) environment and social dimension, (c) resource and social dimension, and (d) resource and environment dimension.

We summarize the formulated strategy for improving sugarcane agroindustry supply chain sustainability as follows: improving the supply chain agility and flexibility to achieve raw material availability by an engineering assessment to understand the current mill efficiency situation to plan for a new facility or machinery revitalization, supply chain

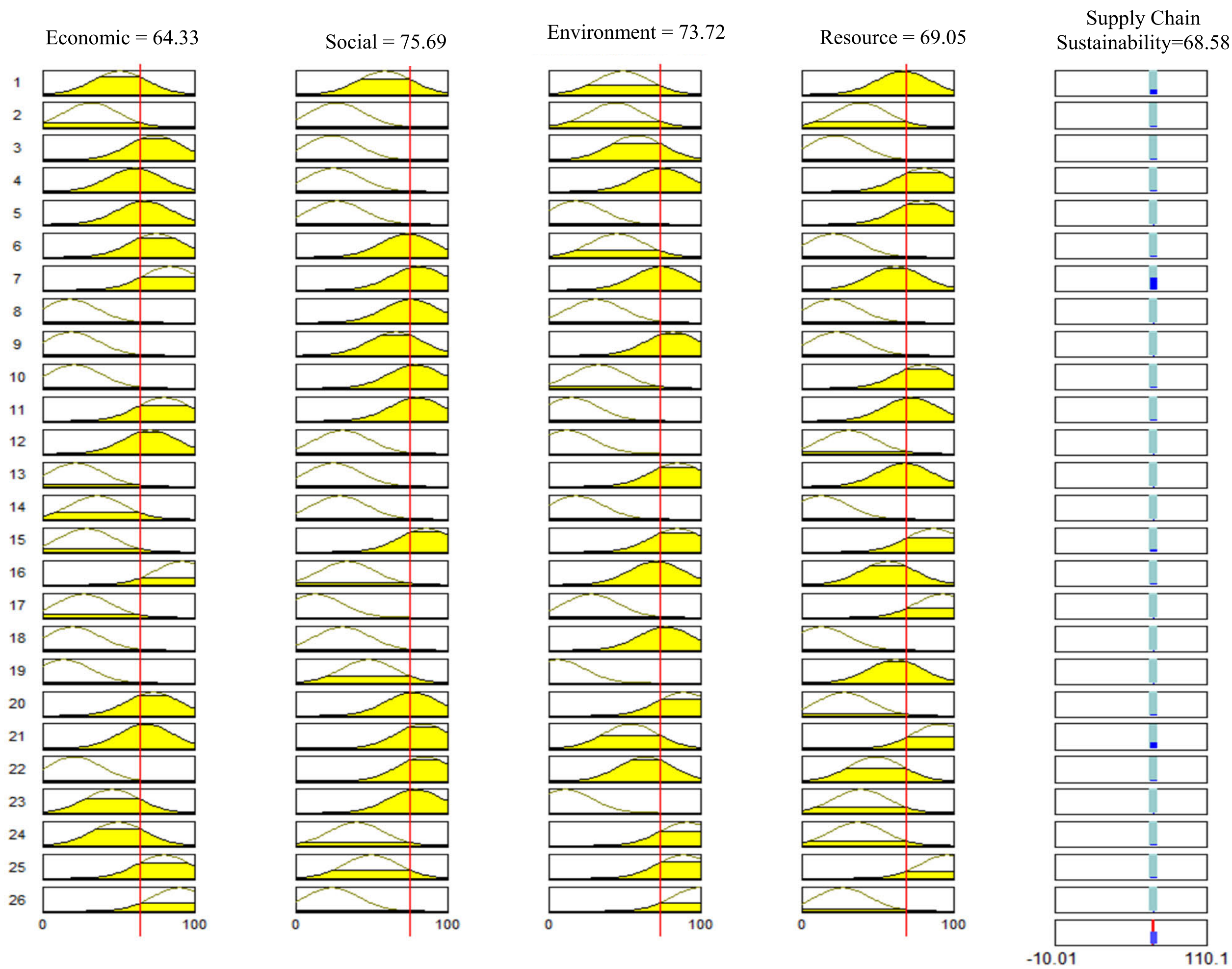

FIGURE 12. Sustainability assessment simulation for sugarcane agroindustry supply chain.

stakeholders' coordination, collaboration in risk management and fair profit allocation, and maintenance of a partnership program with incentives and services for sugarcane farmers.

E. MANAGERIAL IMPLICATION

This study provides managerial insights for the industry to implement sustainable development. Assessments of sustainability are crucial for sustainable development. This study developed and validated an adaptive model to assess the sustainability of the sugarcane supply chain. The model can adaptively provide supply chain sustainability performance to implement in supply chains, which are things to be prepared.

Management must provide a section to monitor sustainability actively and collect data. For easy access to the data by all supply chain stakeholders, the focal company (in this case, the sugar mill) must actively collaborate and coordinate with others. Specific data might be available from suppliers or distributors, although most data and information are available at the focal company. The indicator data obtained from the secondary and primary data were both qualitative and quantitative. Secondary data, which are available in the production data, are easily accessed by the company. Primary data were obtained from expert assessment. This information must be updated periodically to ensure consistency with the current conditions.

To achieve a sustainable supply chain, the sugarcane agro-industry must focus on all dimensions. Often, the economic dimension, which has the lowest sustainability performance, can also affect the other sustainability dimensions. To improve sustainability, managers should concentrate on all dimensions and indicators with a focus on the performance of the lowest indicator. From a complementary perspective, the industry should realign its business and supply chain into sustainability goals if unsustainable performance is found to achieve global competitiveness.

Improvement strategies have been proposed for supply chain sustainability based on key indicators and validated by a group expert. In the implementation of a supply chain, stakeholders should be involved in the system. Sugar mills

TABLE 10. The improvement strategy for supply chain sustainability.

No	Key Indicators	CAM	Proposed strategy
1	Agility performance	0.142	Improve the supply chain flexibility related to the sugarcane availability.
2	Supply chain risk	0.149	Conducted the risk assessment and formulated the improvement strategy. The potential risk must be listed and updated.
3	Profit allocation	0.169	The main goal is to increase the profit. Mill efficiency is the key activity in increasing the profit and maintaining fair profit allocation
4	Institutional support	0.163	Coordinated with the research center and financial organization.
5	CSR	0.163	Maintain the partnership program and
6	Stakeholder partnership	0.166	provide a good financial service in the harvesting season
7	Ambient Air quality	0.148	Improve the mill efficiency through overall recovery. Applied
8	Noise level	0.161	technological used in improving the
9	Solid waste	0.166	environmental impact and conducting improvement strategy.
10	Sugarcane field conversion	0.142	Maintain the partnership program and provide a good financial service in the harvesting season
11	Labor competitive performance	0.165	Conducting an effective training program in improving the mill efficiency.
12	Overall recovery	0.166	Conducting the engineering assessment for the mill condition. The mill condition must improve with two approach, mill revitalization or invest for the new facility

play a significant role in the strategy implementation. Other primary supply chain stakeholders should be coordinated in the implementation, involving sugarcane farmers, cooperative organizations, associations, and distributors. After that, the secondary stakeholders are also coordinated to ensure the supply chain activities run well.

IV. CONCLUSION AND RECOMMENDATION

A. CONCLUSION

This study designed an integrated fuzzy multi-criteria model for sustainability assessment of the sugarcane agroindustry supply chain based on FIS and ANFIS. Strategies for maintaining supply chain sustainability have also been proposed, based on sustainability assessment results and expert group panel discussions. The proposed sustainability assessment model is more accurate and applicable than typical MDS and linear models.

The developed FIS model could assess the sustainability performance of the sugarcane agroindustry supply chain on each dimension, that is, economic, social, environmental, and resource, as 64.33% (almost sustainable), 75.69% (almost sustainable), 73.72% (almost sustainable), and 69.05% (almost sustainable). The FIS model was compared with the current MDS to assess the sustainability assessment and linear calculation models. The proposed FIS model yielded a more accurate value, that is, the lowest error value.

The ANFIS with subtractive clustering initiation model was designed to aggregate supply chain sustainability performance in each dimension. The ANFIS model showed a lower training and testing error, which implied that it was capable of aggregating supply chain sustainability performance with better results. Model validation showed that the overall supply chain sustainability performance of the sugarcane agroindustry was 68.58%, which implied that it was almost sustainable.

This study also proposes a strategy to improve supply chain sustainability performance by focusing on key indicators. The main strategy suggested is maintaining the sugarcane supply by strengthening the partnership program and improving the mill's overall recovery, followed by factory revitalization or new factory investment.

B. RECOMMENDATIONS

Using the proposed model, the individual dimensions, as well as the overall sustainability of the sugarcane supply chain sustainability performance can be determined. This study also proposed a strategy to improve sustainability. However, there is a need for a detailed requirements analysis and engineering assessments. The role of supply chain stakeholders in improving overall supply chain sustainability performance should be assessed and developed.

This study was limited to sugarcane factories that have partnerships with farmers to provide sugarcane resources. How this partnership should be strengthened still needs to be investigated.

Moreover, the proposed model can be applied to other commodities supply chain sustainability performance improvements, such as the palm oil agroindustry supply chain, by indicator adjustment.

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REFERENCES

[1] G. B. H. Brundtland, "Our common future: Report of the world commission on environment and development," *United Nations Commun.*, vol. 4, no. 1, p. 300, 1987, doi: 10.1080/07488008808408783.

[2] R. B. Johnston, "Arsenic and the 2030 Agenda for sustainable development," *Arsen. Res. Glob. Sustain. Proc. 6th Int. Congr. Arsen. Environ. AS*, 2016, pp. 12–14, doi: 10.1201/b20466-7.

[3] E. Grigoroudis, V. S. Kouikoglou, and Y. A. Phillis, "SAFE 2013: Sustainability of countries updated," *Ecological Indicators*, vol. 38, pp. 61–66, Mar. 2014, doi: 10.1016/j.ecolind.2013.10.022.

[4] Y. A. Phillis, V. S. Kouikoglou, and C. Verdugo, "Urban sustainability assessment and ranking of cities," *Comput., Environ. Urban Syst.*, vol. 64, pp. 254–265, Jul. 2017, doi: 10.1016/j.compenvurbsys.2017.03.002.

[5] P. Papilo, Marimin, E. Hambali, and I. S. Sitanggang, "Sustainability index assessment of palm oil-based bioenergy in Indonesia," *J. Cleaner Prod.*, vol. 196, pp. 808–820, Sep. 2018, doi: 10.1016/J.JCLEPRO.2018.06.072.

[6] M. Asrol, P. Papilo, and F. E. Gunawan, "Support vector machine with K-fold validation to improve the industry's sustainability performance classification," *Proc. Comput. Sci.*, vol. 179, pp. 854–862, Jan. 2021, doi: 10.1016/j.procs.2021.01.074.

[7] S. Kot, ''Sustainable supply chain management in small and medium enterprises,'' *Sustainability*, vol. 10, no. 4, pp. 1–19, Apr. 2018, doi: 10.3390/su10041143.

[8] S. Ahmad, K. Wong, and B. Zaman, ''A comprehensive and integrated stochastic-fuzzy method for sustainability assessment in the Malaysian food manufacturing industry,'' *Sustainability*, vol. 11, no. 4, p. 948, Feb. 2019, doi: 10.3390/su11040948.

[9] C. Persada, S. R. Sitorus, M. Marimin, and R. Djakapermana, ''Determination sustainability status in urban infrastructure and policy recommendation for development case study: Bandarlampung City,'' *Civ. Enviromental Res.*, vol. 6, no. 12, pp. 49–60, 2014.

[10] F. S. Wiryawan, Marimin, and T. Djatna, ''Value chain and sustainability analysis of fresh-cut vegetable: A case study at SSS Co,'' *J. Cleaner Prod.*, vol. 260, Jul. 2020, Art. no. 121039, doi: 10.1016/j.jclepro.2020.121039.

[11] S. Bonilla, H. Silva, M. T. da Silva, R. F. Gonçalves, and J. Sacomano, ''Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges,'' *Sustainability*, vol. 10, no. 10, p. 3740, Oct. 2018, doi: 10.3390/SU10103740.

[12] F. Tonelli, S. Evans, and P. Taticchi, ''Industrial sustainability: Challenges, perspectives, actions,'' *Int. J. Bus. Innov. Res.*, vol. 7, no. 2, pp. 143–163, 2013, doi: 10.1504/IJBIR.2013.052576.

[13] M. V. Ciasullo, G. Maione, C. Torre, and O. Troisi, ''What about sustainability? An empirical analysis of consumers' purchasing behavior in fashion context,'' *Sustainability*, vol. 9, no. 9, pp. 1–18, 2017, doi: 10.3390/su9091617.

[14] S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, ''Blockchain technology and its relationships to sustainable supply chain management,'' *Int. J. Prod. Res.*, vol. 57, no. 7, pp. 2117–2135, Apr. 2019, doi: 10.1080/00207543.2018.1533261.

[15] E. Koberg and A. Longoni, ''A systematic review of sustainable supply chain management in global supply chains,'' *J. Cleaner Prod.*, vol. 207, pp. 1084–1098, Jan. 2019, doi: 10.1016/j.jclepro.2018.10.033.

[16] S. Seuring and M. Müller, ''From a literature review to a conceptual framework for sustainable supply chain management,'' *J. Cleaner Prod.*, vol. 16, no. 15, pp. 1699–1710, Oct. 2008, doi: 10.1016/j.jclepro.2008.04.020.

[17] A. Sopadang, S. Wichaisri, and R. Banomyang, ''Sustainable supply chain performance measurement a case study of the sugar industry,'' in *Proc. Int. Conf. Ind. Eng. Oper. Manage.*, Apr. 2017, pp. 335–348.

[18] M. Varsei and S. Polyakovskiy, ''Sustainable supply chain network design: A case of the wine industry in Australia,'' *Omega*, vol. 66, pp. 236–247, Jan. 2017, doi: 10.1016/j.omega.2015.11.009.

[19] A. Fauzi, *Teknik Analisis Keberlanjutan*. Jakarta, Indonesia: PT Gramedia Pustaka Utama, 2019.

[20] M. L. M. Graymore, A. M. Wallis, and A. J. Richards, ''An index of regional sustainability: A GIS-based multiple criteria analysis decision support system for progressing sustainability,'' *Ecol. Complex.*, vol. 6, no. 4, pp. 453–462, Dec. 2009, doi: 10.1016/j.ecocom.2009.08.006.

[21] N. Yakovleva, J. Sarkis, and T. W. Sloan, ''Sustainability indicators for the food supply chain,'' in *Environmental Assessment and Management in the Food Industry*. Cambridge, U.K.: Woodhead Publishing, 2010, pp. 297–330.

[22] A. R. Hemdi, M. Z. M. Saman, and S. Sharif, ''Sustainability evaluation using fuzzy inference methods,'' *Int. J. Sustain. Energy*, vol. 32, no. 3, pp. 169–185, Jun. 2013.

[23] T. Waas, J. Hugé, T. Block, T. Wright, F. Benitez-Capistros, and A. Verbruggen, ''Sustainability assessment and indicators: Tools in a decision-making strategy for sustainable development,'' *Sustainability*, vol. 6, no. 9, pp. 5512–5534, Aug. 2014, doi: 10.3390/su6095512.

[24] J. Edwards, K. McCurley, and J. Tomlin, ''An adaptive model for optimizing performance of an incremental Web crawler,'' in *Proc. 10th Int. Conf. World Wide Web (WWW)*, 2001, pp. 106–113, doi: 10.1145/371920.371960.

[25] R. M. C. Ratnayake, ''Application of a fuzzy inference system for functional failure risk rank estimation: RBM of rotating equipment and instrumentation,'' *J. Loss Prevention Process Industries*, vol. 29, pp. 216–224, May 2014, doi: 10.1016/j.jlp.2014.03.002.

[26] C. Sattler, U. J. Nagel, A. Werner, and P. Zander, ''Integrated assessment of agricultural production practices to enhance sustainable development in agricultural landscapes,'' *Ecol. Indicators*, vol. 10, no. 1, pp. 49–61, Jan. 2010, doi: 10.1016/j.ecolind.2009.02.014.

[27] Y. Tan, C. Shuai, L. Jiao, and L. Shen, ''An adaptive neuro-fuzzy inference system (ANFIS) approach for measuring country sustainability performance,'' *Environ. Impact Assessment Rev.*, vol. 65, pp. 29–40, Jul. 2017, doi: 10.1016/j.eiar.2017.04.004.

[28] B. Khoshnevisan, S. Rafiee, M. Omid, and H. Mousazadeh, ''Development of an intelligent system based on ANFIS for predicting wheat grain yield on the basis of energy inputs,'' *Inf. Process. Agricult.*, vol. 1, no. 1, pp. 14–22, Aug. 2014, doi: 10.1016/j.inpa.2014.04.001.

[29] T. J. Ross, *Fuzzy Logic With Engineering Applications Third Edition*. Chichester U.K.: Wiley, 2010.

[30] J. Van der Vorst and J. Snels, ''Developments and needs for sustainable agro-logistics in developing countries,'' *World Bank Position Note*, vol. 26, Jan. 2014. [Online]. Available: https://openknowledge.worldbank.org/handle/10986/17834

[31] A. M. G. Cornelissen, J. Berg, W. J. Koops, M. Grossman, and H. M. J. Udo, ''Assessment of sustainable development: A novel approach using fuzzy set theory,'' *J. Econ. Lit.*, vol. 2000, pp. 1–17, Aug. 2000. [Online]. Available: https://www.erim.eur.nl

[32] *Statistik Tebu Indonesia 2017*, Badan Pusat Statistik, BPS, Jakarta, Indonesia, 2018.

[33] M. Asrol, M. Marimin, M. Machfud, and M. Yani, ''Method and approach mapping of fair and balanced risk and value-added distribution in supply chains: A review and future agenda,'' *Int. J. Supply Chain Manag.*, vol. 7, no. 5, pp. 74–95, 2018. [Online]. Available: https://excelingtech.co.U.K./

[34] L. M. Fonseca and V. M. Lima, ''Impact of supplier management strategies on the organizational performance of ISO 9001 certified organizations,'' *Qual. Innov. Prosperity*, vol. 19, no. 2, pp. 32–54, 2015, doi: 10.12776/qip.v19i2.592.

[35] I. Juwana, N. Muttil, and B. J. C. Perera, ''Indicator-based water sustainability assessment—A review,'' *Sci. Total Environ.*, vol. 438, pp. 357–371, Nov. 2012, doi: 10.1016/j.scitotenv.2012.08.093.

[36] P. Ghadimi, A. H. Azadnia, N. M. Yusof, and M. Z. M. Saman, ''A weighted fuzzy approach for product sustainability assessment: A case study in automotive industry,'' *J. Cleaner Prod.*, vol. 33, pp. 10–21, Sep. 2012, doi: 10.1016/j.jclepro.2012.05.010.

[37] C. Peano, P. Migliorini, and F. Sottile, ''A methodology for the sustainability assessment of agri-food systems: An application to the slow food presidia project,'' *Ecol. Soc.*, vol. 19, no. 4, pp. 24–35, 2014.

[38] N. M. Galal and A. F. A. Moneim, ''Developing sustainable supply chains in developing countries,'' *Proc. CIRP*, vol. 48, pp. 419–424, Jan. 2016, doi: 10.1016/j.procir.2016.03.156.

[39] T. Popovic, A. Barbosa-Póvoa, A. Kraslawski, and A. Carvalho, ''Quantitative indicators for social sustainability assessment of supply chains,'' *J. Cleaner Prod.*, vol. 180, pp. 748–768, Apr. 2018, doi: 10.1016/j.jclepro.2018.01.142.

[40] S. Ahmad and K. Y. Wong, ''Development of weighted triple-bottom line sustainability indicators for the Malaysian food manufacturing industry using the delphi method,'' *J. Cleaner Prod.*, vol. 229, pp. 1167–1182, Aug. 2019, doi: 10.1016/j.jclepro.2019.04.399.

[41] *Pedoman Teknis Pengembangan Tebu*. Direktorat Jenderal Perkebunan, Kementerian Perdagangan RI, Jakarta, Indonesia, 2013.

[42] M. Kadwa, ''An overview of sugarcane supply chain inconsistencies [disertasi],'' Ph.D. dissertation, Univ. KwaZulu-Natal, Pietermaritzburg, South Africa, 2013.

[43] M. Fahrizal, M. Yani, M. Y. J. Purwanto, and Sumaryanto, ''Model penunjang keputusan pengembangan agroindustri gula tebu (studi kasus di Provinsi Nusa Tenggara Timur),'' *J. Teknol. Ind. Pertan.*, vol. 24, no. 3, pp. 189–199, 2014.

[44] D. Yunitasari, D. B. Hakim, B. Juanda, and R. Nurmalina, ''Menuju swasembada gula nasional: Model kebijakan untuk meningkatkan produksi gula dan pendapatan petani tebu di Jawa Timur,'' *J. Ekon. Kebijak. publik*, vol. 6, no. 1, pp. 1–15, 2015.

[45] T. Dewayana, S. Ma'arif, S. Sukardi, and S. Raharja, ''Rancang bangun model pengukuran kinerja pabrik gula,'' *J. Tek. Ind.*, vol. 5, no. 3, pp. 151–228, 2010.

[46] S. Subiyanto, ''Analisis efektifitas mesin/alat pabrik gula menggunakan metode overall equipments effectiveness,'' *Jurnal Teknik Industri*, vol. 16, no. 1, pp. 43–52, May 2014, doi: 10.9744/jti.16.1.43-52.

[47] R. Jaya, M. Machfud, S. Raharja, and M. Marimin, ''Sustainability analysis for gayo coffee supply chain,'' *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 3, no. 2, pp. 24–28, 2013.

[48] *Model Perencanaan Agroindustri Gula Tebu Lahan Kering Berkelanjutan di Provinsi Nusa Tenggara Timur [Disertasi]*, Fahrizal, Institut Pertanian Bogor, Bogor, Indonesian, 2015.

[49] H. Hardjomidjojo, S. Raharja, and M. Chosyi'ah, ''Pengukuran indeks keberlanjutan industri gula,'' *MANAJEMEN IKM, Jurnal Manajemen Pengembangan Industri Kecil Menengah*, vol. 11, no. 1, pp. 89–96, Aug. 2016.

[50] A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, pp. 338–353, Jan. 1965, doi: 10.1016/S0019-9958(65)90241-X.

[51] Y. A. Phillis and L. A. Andriantiatsaholiniaina, "Sustainability: An ill-defined concept and its assessment using fuzzy logic," *Ecol. Econ.*, vol. 37, no. 3, pp. 435–456, Jun. 2001.

[52] M. J. Muñoz, J. M. Rivera, and J. M. Moneva, "Evaluating sustainability in organisations with a fuzzy logic approach," *Ind. Manage. Data Syst.*, vol. 108, no. 6, pp. 829–841, Jun. 2008, doi: 10.1108/02635570810884030.

[53] R. R. Yager, "On ordered weighted averaging aggregation operators in multicriteria decisionmaking," *IEEE Trans. Syst., Man, Cybern.*, vol. 18, no. 1, pp. 183–190, Jan. 1988, doi: 10.1109/21.87068.

[54] Marimin, M. Umano, I. Hatono, and H. Tamura, "Linguistic labels for expressing fuzzy preference relations in fuzzy group decision making," *IEEE Trans. Syst. Man, Cybern. B Cybern.*, vol. 28, no. 2, pp. 205–218, Apr. 1998, doi: 10.1109/3477.662760.

[55] Y. A. Phillis, E. Grigoroudis, and V. S. Kouikoglou, "Sustainability ranking and improvement of countries," *Ecol. Econ.*, vol. 70, no. 3, pp. 542–553, Jan. 2011, doi: 10.1016/j.ecolecon.2010.09.037.

[56] T. J. Pitcher and D. Preikshot, "Rapfish: A rapid appraisal technique to evaluate the sustainability status of fisheries," *Fisheries Res.*, vol. 49, no. 3, pp. 255–270, Jan. 2001.

[57] J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst., Man, Cybern.*, vol. 23, no. 3, pp. 665–685, Jun. 1993.

[58] S. Kusumadewi and H. Purnomo, *Aplikasi Logika Fuzzy Untuk Pendukung Keputusan*. Yogyakarta, Indonesia: Graha Ilmu, 2004.

[59] A. Moghaddamnia, M. G. Gousheh, J. Piri, S. Amin, and D. Han, "Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques," *Adv. Water Resour.*, vol. 32, no. 1, pp. 88–97, Jan. 2009, doi: 10.1016/j.advwatres.2008.10.005.

[60] W. Sun, P. Hu, F. Lei, N. Zhu, and Z. Jiang, "Case study of performance evaluation of ground source heat pump system based on ANN and ANFIS models," *Appl. Thermal Eng.*, vol. 87, pp. 586–594, Aug. 2015, doi: 10.1016/j.applthermaleng.2015.04.082.

[61] S. Ahmad and M. Jamshed, "Sustainable agriculture through supply chain risk management in India," in *Proc. Int. Conf. Global Bus., Econ., Finance Social Sci. (GB15 Kolkata Conference)*, 2015, pp. 18–20.

[62] A. Jamali, N. Nariman-zadeh, H. Ashraf, and Z. Jamali, "Robust Pareto design of ANFIS networks for nonlinear systems with probabilistic uncertainties," in *Proc. Int. Symp. Innov. Intell. Syst. Appl.*, Jun. 2011, pp. 300–304.

[63] K. Kokkinos, E. Papageorgiou, V. Dafopoulos, and A. Ioannis, "Efficiency in energy decision support systems using soft computing techniques," in *Intelligent Decision Support Systems for Sustainable Computing*, A. Kumar, S. Ajith, A. Patrick, and S. Michael, Eds. Cham, Switzerland: Springer, 2017, pp. 33–52.

[64] Y.-M. Wang and T. M. S. Elhag, "An adaptive neuro-fuzzy inference system for bridge risk assessment," *Expert Syst. Appl.*, vol. 34, no. 4, pp. 3099–3106, 2008, doi: 10.1016/j.eswa.2007.06.026.

[65] R. G. Sargent, "Verification and validation of simulation models," *J. Simul.*, vol. 7, no. 1, pp. 12–24, Feb. 2013, doi: 10.1057/jos.2012.20.

[66] M. Asrol, M. Marimin, M. Machfud, M. Yani, and E. Taira, "Supply chain fair profit allocation based on risk and value added for sugarcane agro-industry," *Oper. Supply Chain Manage., Int. J.*, vol. 13, no. 2, pp. 150–165, Mar. 2020.

[67] G. A. Mendoza and R. Prabhu, "Qualitative multi-criteria approaches to assessing indicators of sustainable forest resource management," *For. Ecol. Manage.*, vol. 174, nos. 1–3, pp. 329–343, 2003, doi: 10.1016/S0378-1127(02)00044-0.

[68] S. S. Chauhan and J.-M. Proth, "Analysis of a supply chain partnership with revenue sharing," *Int. J. Prod. Econ.*, vol. 97, no. 1, pp. 44–51, Jul. 2005, doi: 10.1016/j.ijpe.2004.05.006.

[69] S. Suharjito and M. Marimin, "Risks balancing model of agri-supply chain using fuzzy risks utility regression," *J. Theor. Appl. Inf. Technol.*, vol. 41, no. 2, pp. 134–144, 2012.

[70] R. Astuti, Marimin, R. Poerwanto, Machfud, and Y. Arkeman, "Kebutuhan dan struktur kelembagaan rantai pasok manggis," *J. Manaj. Bisnis*, vol. 3, no. 1, pp. 99–115, 2010.

[71] W. K. D. Cahyani, M. Marimin, and S. Sukardi, "Model produktivitas bagi hasil agroindustri gula tebu dalam kemitraan antara petani dan perusahaan: Studi kasus Di PG Kremboong, Sidoarjo," *J. Teknol. Ind. Pertan.*, vol. 27, no. 2, pp. 114–124, 2017, doi: 10.24961/j.tek.ind.pert.2017.27.2.114.

[72] *Supply Chain Operations Reference Model Revision 11.0.*, Supply Chain Council, SCC, New York, NY, USA, 2012.

[73] N. Rusono, *Studi Pendahuluan Rencana Pembangunan Jangka Menengah Nasional (RPJMN) Bidang Pangan dan Pertanian 2015–2019*. Jakarta, Indonesia: Direktorat Pangan dan Pertanian, 2014.

[74] *Statistik Tebu Indonesia 2016*, BPS, Badan Pusat Statistik, Jakarta, Indonesia, 2017.

[75] N. P. Miefthawati and I. Muhadi, "Analisis estimasi emisi gas rumah kaca pada pembangkit listrik thermal di Provinsi Riau tahun 2016–2020," in *Seminar Nasional Teknik Elektro 2018*. Pekanbaru, Indonesia: UIN Sultan Syarif Kasim, 2018, pp. 50–53.

[76] S. Putt and P. Bhatia, *Working 9 to 5 on Climate Change?: An Office Guide*. Washington, DC, USA: World Resource Institute, 2002.

[77] T. Ramjeawon, "Life cycle assessment of electricity generation from bagasse in Mauritius," *J. Cleaner Prod.*, vol. 16, no. 16, pp. 1727–1734, Nov. 2008, doi: 10.1016/j.jclepro.2007.11.001.

[78] I. Hermawan and R. Rasbin, "Analisis penggunaan luas Lahan tebu dan padi terkait pencapaian swasembada gula di Indonesia," *J. Ekon. Kebijak. publik*, vol. 3, no. 1, pp. 47–63, 2012.

[79] A. Mulyani, D. Kuncoro, D. Nursyamsi, and F. Agus, "Analisis konversi Lahan sawah: Penggunaan data spasial resolusi tinggi memperlihatkan laju konversi Yang mengkhawatirkan," *J. Tanah Iklim*, vol. 40, no. 2, pp. 121–133, 2016.

[80] T. Bantacut, "Swasembada gula?: Prospek dan strategi pencapaiannya," *Pangan*, vol. 19, no. 3, pp. 245–256, 2010, doi: 10.1016/j.amjmed.2009.04.007.

[81] *Prefeasibility Study: Identifikasi Peluang Investasi Pengembangan Industri Gula di Indonesia*, Badan Koordinasi Penanaman Modal, BKPM, Jakarta, Indonesia, 2015.

[82] E. Houshyar, M. J. SheikhDavoodi, M. Almassi, H. Bahrami, H. Azadi, M. Omidi, G. Sayyad, and F. Witlox, "Silage corn production in conventional and conservation tillage systems. Part I: Sustainability analysis using combination of GIS/AHP and multi-fuzzy modeling," *Ecol. Indicators*, vol. 39, pp. 102–114, Apr. 2014, doi: 10.1016/j.ecolind.2013.12.002.

[83] J. Jassbi, S. Seyedhosseini, and N. Pilevari, "An adaptive neuro fuzzy inference system for supply chain agility evaluation," *Int. J. Ind. Eng. Prod. Res.*, vol. 20, no. 4, pp. 187–196, 2010.

[84] I. Vanany, S. Zailani, and N. Pujawan, "Supply chain risk management: Literature review and future research," *Int. J. Inf. Syst. Supply Chain Manage.*, vol. 2, no. 1, pp. 16–33, Jan. 2009, doi: 10.4018/jisscm.2009010102.

[85] M. Amad-Saeed and W. Kersten, "Supply chain sustainability performance indicators—A content analysis based on published standards and guidelines," *Logist. Res.*, vol. 2017, no. 10, p. 12, 2017, doi: 10.23773/2017.

[86] N. Yakovleva, J. Sarkis, and T. Sloan, "Sustainable benchmarking of supply chains: The case of the food industry," *Int. J. Prod. Res.*, vol. 50, no. 5, pp. 1297–1317, Mar. 2012, doi: 10.1080/00207543.2011.571926.

[87] F. Bunte, "Pricing and performance in agri-food supply chains," in *Proc. Frontis Workshop Quantifying Agri-Food Supply Chain*, no. 15, Oct. 2004, pp. 39–47, doi: 10.1007/1-4020-4693-6_4.

[88] E. K. Lestari, *Efisiensi dan Kerangka Kelembagaan Tebu Rakyat Dalam Mendukung Perekonomian Wilayah di Kabupaten Jember [Disertasi]*. Bogor, Indonesia: Institut Pertanian Bogor, 2015.

[89] S. Yuniati, D. Susilo, and F. Albayumi, "Penguatan kelembagaan dalam upaya meningkatkan kesejahteraan petani tebu," in *Proc. Prosiding Seminar Nasional dan Call Paper Ekonomi dan Bisnis*, Oct. 2017, pp. 498–505.

[90] H. L. C. Coutinho, A. P. D. Turetta, J. M. G. Monteiro, S. S. de Castro, and J. P. Pietrafesa, "Participatory sustainability assessment for sugarcane expansion in Goiás, Brazil," *Sustainability*, vol. 9, no. 9, pp. 1–15, 2017, doi: 10.3390/su9091573.

[91] A. D. Ross, H. Parker, M. del Mar Benavides-Espinosa, and C. Droge, "Sustainability and supply chain infrastructure development," *Manage. Decis.*, vol. 50, no. 10, pp. 1891–1910, Nov. 2012, doi: 10.1108/00251741211279666.

[92] S. Santiteerakul and A. Sekhari, "Social indicators for sustainable supply chain performance measurement," in *Proc. Int. Conf. Softw., Knowl., Inf. Manage. Appl.*, Sep. 2011, pp. 1–6.

[93] R. A. Hadiguna, *Manajemen Rantai Pasok Agroindustri?*. Padang, Indonesia: Andalas Univ. Press, 2016.

[94] *The United Nations Framework Convention on Climate Change*, United Nations Framework Conv. Climate Change, Bonn, Germany, 2006.

[95] *IPCC Guidelines for National Greenhouse Gas Inventories*, Kanagawa, Kanagawa Ward, Intergovernmental Panel Climate Change, 2006.

[96] M. A. Renouf, M. K. Wegener, and L. K. Nielsen, "An environmental life cycle assessment comparing Australian sugarcane with U.S. Corn and U.K. Sugar beet as producers of sugars for fermentation," *Biomass Bioenergy*, vol. 32, no. 12, pp. 1144–1155, Dec. 2008, doi: 10.1016/j.biombioe.2008.02.012.
[97] A. Azapagic and S. Perdan, "Indicators of sustainable development for industry," *Process Saf. Environ. Protection*, vol. 78, no. 4, pp. 243–261, Jul. 2000, doi: 10.1205/095758200530763.
[98] *Indicators of Sustainable Development?: Guidelines and Methodologies*, United Nations, New York, NY, USA, Oct. 2007.

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