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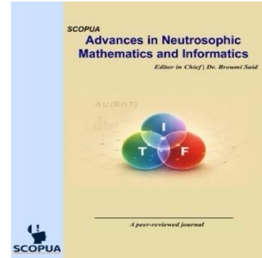

Adaptive Neuro Neutrosophic Inference System for Sustainable Supplier Selection

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ABSTRACT

Sustainable supplier selection is one of the critical decision-making problems in eco-centric supply chain management system. The existing traditional decision-making methods fail to address the inherent uncertainty, imprecision and indeterminacy. This study proposes Adaptive Neuro-Neutrosophic Inference System (ANNIS) to address these challenges. The proposed framework blends neural networks with neutrosophic logic to evolve an intelligent decision support system. The ANNIS model considers multifaceted criteria for supplier selection with rule based neutrosophic inference architecture. The effectiveness of ANNIS is compared with fuzzy inferences with special reference to accuracy, decision consistency, stability and reliability. The results exhibit the efficacy of ANNIS in handling complex decision making environments.

Keywords: ANNIS; Neutrosophic logic; Supplier selection; Sustainability

1. Introduction

The modern supply chain management system is governed with the principles of sustainability. The three pillars of sustainability namely People, Profit and Planet serve as the core principles of industrial functioning. The decision making on sustainable supplier selection is intricate as the scenario is inherited with uncertainty and indeterminacy. The criteria ascertained to choose the supplier varies across the industries, however, the criteria such as cost, quality, reliability, flexibility and environmental sustainability continue to be the primary priorities. The circumstances of decision making become further complex if the decision makers compete with conflicting criteria. One of the key reasons of complexity, is the cause of disparities in ranking the criteria. On other hand, lack of precise representation of the supplier's information may not give a complete picture of the data. This has emerged the need of evolving an integrated decision framework blending neural network architecture with fuzzy inferences.

Researchers have applied Adaptive neuro fuzzy inference system in supplier selection. To mention a few, Guneri et al. [1] developed ANFIS based input selection and modeling, Okwu and Tartibu [2] discussed the integrated approach of TOPSIS and ANFIS in sustainable supplier selection in retail industry. Khaldi et al. [3] discussed prediction of supplier performance using a novel approach of DEA- ANFIS. Asgari et al. [4] compared the efficacy of ANFIS with fuzzy based multi-criteria decision making in supplier selection. Khalili et al. [5] developed a two-stage approach blending ANFIS and fuzzy goal programming in supplier selection. Arantes et al. [6] formulated group decision based approach of ANFIS in supplier selection. Though these ANFIS models, handle uncertainty, the component of indeterminacy remains unaddressed. To handle this shortcoming, researchers have extended neural network modeling with neutrosophic inference. Alqahtani et al. [7] applied ANNIS to handle intricacy in portfolio optimization. Ibrahim et al. [8] applied in hate speech detection. Huang et al. [9] employed ANNIS in comprehending neural dynamics. Jerbi et al. [10] discussed the application of ANNIS in acoustic source tracking. Saravanaraj and Govindan [11] leveraged in financial sentiment analysis. Mourtas et al. [12] discussed adaptive recurrent neural network with neutrosophic representations. Muratoglu and Organ [13] used ANFIS for sustainable supplier selection and improved supplier evaluation accuracy. Esmaeilzadeh et al. [14] applied ANFIS with meta-heuristic algorithms for supplier development in the automotive industry. Florentin Smarandache [15] (introduced neutrosophic logic to manage uncertainty and indeterminacy in decision-making.

The ANNIS based modelling is gaining momentum as it outsmarts ANFIS in terms of handling indeterminacy. However few research gaps exist based on the aforementioned literature. The ANNIS is model is not discussed in sustainable supplier selection to the best of our knowledge and no comparative analysis is also performed in this context. This has motivated the authors to develop ANNIS decision making model in sustainable supplier selection. The remaining contents of the work are organized as follows. Section 2 presents the preliminaries of neutrosophic. Section 3 discusses the methodology of ANNIS. Section 4 applies the decision framework of ANNIS in sustainable supplier selection. Section 5 discusses the results and the last section concludes the work.

2. Preliminaries

This section presents the basic definitions related to neutrosophic logic.

2.1 Neutrosophic set

Let X be a space of points (objects) and $x \in X$. A neutrosophic set A in X is defined by a truth-membership function$T_A(x)$, an indeterminacy membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. $T_A(x), I_A(x)$ and $F_A(x)$ are real standard or real nonstandard subsets of $]0^-, 1^+[$. That is $T_A(x): X \to]0^-, 1^+[$, $I_A(x): X \to]0^-, 1^+[$ and $F_A(x): X \to]0^-, 1^+[$. There is not restriction on the sum of $T_A(x), I_A(x)$ and $F_A(x)$, so $0^- \leq sup\ T_A(x) \leq sup\ I_A(x) \leq sup\ F_A(x) \leq 3+$.

2.2 Single Valued Neutrosophic Set

Let X be a universe of discourse. A single valued neutrosophic set A over X is an object having the form

$$A = \{\langle x,\ T_A(x), I_A(x), F_A(x) : x \in X\ \rangle\}$$

where $T_A(x): X \to [0,1]$, $I_A(x): X \to [0,1]$ and $F_A(x): X \to [0,1]$ with $0 \leq T_A(x), +I_A(x) + F_A(x) \leq 3$ for all $x \in X$. The intervals $T_A(x), I_A(x)$ and $F_A\ (x)$ denote the truth- membership degree, the indeterminacy-membership degree and the falsity membership degree of x to A, respectively.

2.3 Operations on SVNS

The basic arithmetic operations for single-valued neutrosophic numbers (SVNN) are typically defined for addition, multiplication and scalar multiplication. An SVNN is denoted as $A = \langle T, I, F\rangle$, where $T, I,$ and F are the truth, indeterminacy and falsity membership degrees respectively and $T, I, F \in [0,1]$ and $0 \leq T + I + F \leq 3$.

Let two single values neutrosophic numbers be $A_1 = \langle T_1, I_1, F_1\rangle$and $A_2 = \langle T_2, I_2, F_2\rangle$ and $\lambda > 0$ be any real number. The fundamental operations are defined as follows:

- ***Addition***$(\boldsymbol{A_1 \oplus A_2})$: The sum of two SVNN defined by the following membership functions:

$$A_1 \oplus A_2 = \langle T_1 + T_2 - T_1T_2,\ I_1I_2, F_1F_2\rangle$$

- ***Multiplication***$(\boldsymbol{A_1 \otimes A_2})$: The product of two SVNN defined by the following membership functions:

$$A_1 \otimes A_2 = \langle T_1T_2,\ I_1 + I_2 - I_1I_2,\ F_1 + F_2 - F_1F_2\rangle$$

- ***Scalar Multiplication***$(\boldsymbol{\lambda A_1})$:The Scalar multiplication of an SVNN by a scalar λ is defined as:

$$\lambda A_1 = \langle 1 - (1 - T_1)^\lambda, I_1^\lambda, F_1^\lambda\rangle$$

- ***Exponentiation***$\left(\boldsymbol{A_1^\lambda}\right)$:An SVNN raised to the power of a scalar λ is defined as:

$$\boldsymbol{A_1^\lambda = \langle T_1^\lambda, 1 - (1 - I_1)^\lambda, 1 - (1 - F_1)^\lambda\rangle}$$

2.4 Score function

Let $A = \langle T, I, F\rangle$ be a single valued neutrosophic number, a score function S of a single valued neutrosophic value, based on the truth membership degree, indeterminacy-membership degree and falsity membership degree is defined by

$$S(A) = \frac{(2 + \mathrm{T} - \mathrm{I} - \mathrm{F})}{3}$$

Where $S(A) \in [-1,1]$.

3. Methodology of Adaptive Neuro–Neutrosophic Inference System (ANNIS)

This section explores the steps involved in ANNIS. This decision framework is hybrid in nature as it integrates neural networks, neutrosophic theory, adaptive learning and rule-based inference systems. ANNIS framework extends traditional inference system incorporating neutrosophic components of truth, indeterinacy and falsity. The proposed architecture of ANNIS is competent to handle uncertainty, inconsistency and incomplete information present in real-world decision-making environments.

3.1 Problem Definition

Let $X=\{x_1,x_2,\ldots,x_n\}$ be the set of input variables and $Y=\{y_1,y_2,\ldots,y_m\}$ be the output variables. Let F:X→Y be ANNIS mapping of input space into output space such that $Y=\mathrm{F}(X,\Theta)$. Here, Θdenotes adaptive parameters and F signify ANNIS inference mechanism.

3.2 Neutrosophic Representation

Each of the input variables is signified using a three valued logic of the form

$$x_i^N = (T_i, I_i, F_i)$$

where:

- $T_i \in [0,1]$: truth-membership degree,
- $I_i \in [0,1]$: indeterminacy degree,
- $F_i \in [0,1]$: falsity degree.

subject to:

$$0 \le T_i + I_i + F_i \le 3$$

This neutrosophic representation handles uncertain and inconsistent information.

3.3 Construction of ANNIS architecture

The generalized ANNIS architecture comprises of the following layers namely

- Input layer
- Neutrosophic Fuzzification Layer
- Rule Layer
- Normalization Layer
- Adaptive Learning Layer
- Output Layer

Layer 1: Input Layer

The input vector is denoted as:

$$X = (x_1, x_2, \ldots, x_n)$$

where each variable may represent quantitative or qualitative information.

The input layer transits information to the neutrosophic fuzzification layer without any changes.

Layer 2: Neutrosophic Fuzzification Layer

Each input is transformed into neutrosophic membership values.

For input x_i, the membership functions are defined as:

Truth Membership

$$T_i(x) = \mu_T(x_i)$$

Indeterminacy Membership

$$I_i(x) = \mu_I(x_i)$$

Falsity Membership

$$F_i(x) = \mu_F(x_i)$$

A generalized Gaussian membership form is:

$$\mu(x) = exp\left[\frac{(x-c)^2}{2\sigma^2}\right]$$

where:

- c: center parameter,
- σ: spread parameter.

Thus,

$$T_i = exp\left[\frac{-(x_i - c_T)^2}{2\sigma_T^2}\right]$$

$$I_i = exp\left[-\frac{(x_i - c_I)^2}{2\sigma_I^2}\right]$$

$$F_i = exp\left[-\frac{(x_i - c_F)^2}{2\sigma_F^2}\right]$$

The parameters are adaptively updated during learning.

Layer 3: Neutrosophic Rule Base

The ANNIS employs a collection of neutrosophic IF–THEN rules.

A generalized rule $R_k$is defined as:

R_k:

IF

x_1 is A_1^k
AND
x_2 is A_2^k
AND
x_n is A_n^k
THEN
y_k=$f_k(X)$

where:

- A_i^k denotes neutrosophic linguistic variables,
- $f_k(X)$ denotes the consequent function.

The consequent may be linear:

$$f_k(X) = a_0^k + \sum_{i=1}^{n} a_i^k x_i$$

or nonlinear depending on application requirements.

Later 4: Rule Firing Strength

The firing strength of rule $R_k$is determined using neutrosophic aggregation:

$$w_k = \prod_{i=1}^{n} T_i^k (x_i)$$

To incorporate uncertainty and contradiction:

$$w_k = \prod_{i=1}^{n} \left[T_i^k (x_i)(1 - I_i^k (x_i))(1 - F_i^k (x_i))\right]$$

This formulation reduces the influence of uncertain or contradictory information.

Layer 5: Normalization Layer

The normalized firing strength is:

$$\bar{w}_k = \frac{w_k}{\sum_{k=1}^{M} w_k}$$

where:

M : total number of rules.

The normalized strengths satisfy:

$$\sum_{k=1}^{M} \bar{w}_k = 1$$

Layer 6: Adaptive Neural Learning

ANNIS employs adaptive learning to optimize:

- membership parameters,
- rule weights,
- consequent parameters.

The system output is:

$$\hat{Y} = \sum_{k=1}^{M} \bar{w}_k f_k(X)$$

The objective is to minimize prediction error:

$$E = \frac{1}{2} \sum_{p=1}^{N} (Y_p - \hat{Y}_p)^2$$

where:

- Y_p: actual output,
- $\hat{Y}_p$: predicted output.

Parameters are updated using gradient descent:

$$\theta^{new} = \theta^{old} - \eta \frac{\partial E}{\partial \theta}$$

where:

- η : learning rate,
- θ : adaptive parameter set.

Layer 7: Defuzzification and Output Layer

The final ANNIS output is computed as:

$$Y = \sum_{k=1}^{M} \bar{w}_k f_k(X)$$

In this case, the output may represent classification, prediction, ranking, optimization score , decision index.

3.4 Neural Network Learning Structure

The ANNIS framework incorporates a feed-forward neural network structure.

The architecture employed in this study consists of:

- Input neurons = n
- Hidden Layer 1 = 32 neurons
- Hidden Layer 2 = 16 neurons
- Output neurons = m

Rectified Linear Unit (ReLU) activation function is employed in the hidden layers

$$\text{ReLU}(z) = \max(0, z)$$

The output layer uses linear activation for regression problems and softmax activation for classification problems. The neural network studies the nonlinear relationships between neutrosophic features and target outputs.

3.5 Training Procedure

After normalizing the input variables, 70% of the data set is partitioned into training set, 15% into validation set and 15% into testing set. In the training process, the parameters are updated using propagation and the whole procedure is repeated until the convergence is obtained

3.6 Hyperparameter Configuration

The ANNIS model employs the following hyperparameters:

Parameter	Value
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Maximum Epochs	200
Early Stopping Patience	20 Epochs
Hidden Layer 1	32 Neurons
Hidden Layer 2	16 Neurons
Membership Function	Gaussian
Number of Rules	M

These parameters are selected through validation experiments.

4. Application of ANNIS in Supplier Selection

4.1 Problem Definition

Let us consider the set of suppliers to be $S = \{S_1, S_2, S_3, \ldots, S_{50}\}$ from whom the company intends to select the most suitable supplier. Let the sustainable criteria be $C = \{C_1, C_2, C_3, \ldots, C_6\}$, where

- C_1: Cost
- C_2: Quality
- C_3: Delivery Reliability
- C_4: Environmental Performance
- C_5: Social Responsibility
- C_6: Technological Capability

Because expert judgments contain uncertainty and indeterminacy, neutrosophic representation is adopted.

The objective of this decision making problem is to determine the most sustainable supplier. The required input data of supplier evaluation is presented in Table 1.

Furthermore, the criterion values are measured on a 10-point rating scale, where the benefit criteria are assessed based on higher performance values and the lower values indicate better performance of cost criteria. The ratings are obtained using a structured questionnaire through expert assessment involving managerial personnel. The experts such as procurememt managers, sustainability officers and analyst evaluated each supplier based on the historical records of the suppliers, sustainability reports and performance records. Prior to ANNIS implementation all the values of the criteria are normalized into the interval [0,1] using Min-Max normalization to ensure fair comparison.

The normalized value is computed as:
For benefit criteria:

$$x_{ij}^{*} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

For cost criteria:

$$x_{ij}^{*} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$$

where:

- x_{ij}denotes the original value of supplier $i$under criterion j,
- x_{ij}^{*}denotes the normalized value.

Table 1: Initial Input Data of Supplier Evaluation

Supplier	Cost	Quality	Delivery	Environmental	Social	Technology
S_1	4.2	8.5	7.9	8.1	7.4	8.2
S_2	6.1	7.8	8.6	7.2	8.5	7.9
S_3	3.8	9.1	8.8	8.7	7.9	8.8
S_4	5.5	7.4	7.2	6.8	7.1	7.0
S_5	4.9	8.3	8.0	8.4	8.2	8.5
S_6	6.8	6.9	7.5	7.1	6.8	7.3
S_7	3.9	9.0	9.1	8.9	8.7	9.0
S_8	5.7	7.6	7.4	7.0	7.5	7.1
S_9	4.5	8.7	8.3	8.2	8.0	8.6
S_{10}	6.2	7.1	7.0	6.9	7.2	7.4
S_{34}	5.9	7.3	7.1	7.0	7.3	7.2
S_{35}	4.4	8.8	8.5	8.4	8.3	8.7
S_{46}	6.5	6.8	7.2	6.9	6.9	7.0
S_{47}	3.7	9.3	9.2	9.0	8.8	9.2
S_{48}	5.3	7.7	7.8	7.5	7.4	7.8
S_{49}	4.6	8.6	8.4	8.3	8.2	8.5
S_{50}	6.0	7.2	7.1	7.0	7.1	7.3

4.2 Neutrosophic Transformation

For normalized criterion value:

$$x_{ij}^{*} \in [0,1]$$

Truth membership $T_{ij} = x_{ij}^{*}$

Indeterminacy membership $I_{ij} = 1 - | x_{ij}^{*} - 0.5 |$

Falsity membership $F_{ij} = 1 - T_{ij}$

Thus the transformed neutrosophic form is $x_{ij}^{N} = (T_{ij}, I_{ij}, F_{ij})$

ANNIS Rule is given in Tabular form

Rule No.	ANNIS Rule
R1	IF Cost is Low AND Quality is High AND Delivery is High THEN Sustainability is Excellent
R2	IF Cost is Medium AND Environmental Performance is High AND Technology is High THEN Sustainability is Very Good
R3	IF Cost is High AND Quality is Medium THEN Sustainability is Moderate
R4	IF Delivery Reliability is High AND Social Responsibility is High THEN Sustainability is Excellent
R5	IF Environmental Performance is Low THEN Sustainability is Poor
R6	IF Technology Capability is High AND Quality is High THEN Sustainability is Excellent
R7	IF Cost is Low AND Social Responsibility is High THEN Sustainability is Very Good
R8	IF Cost is High AND Environmental Performance is Low THEN Sustainability is Unsustainable

The other steps of this ANNIS Mathematical Model are presented in Table 2.

Table 2: ANNIS in Supplier Selection

The firing strength of rule k	$w_k = \prod_{i=1}^{n} [T_i(x_i)(1 - I_i(x_i))(1 - F_i(x_i))]$
Normalized firing strength	$\bar{w}_k = \frac{w_k}{\sum_{k=1}^{M} w_k}$

ANNIS output	$$Y = \sum_{k=1}^{M} \bar{w}_k f_k(X)$$
Error function	$$E = \frac{1}{2}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$
Parameter update	$$\theta^{new} = \theta^{old} - \eta \frac{\partial E}{\partial \theta}$$

4.3 Experimental Setup

Python programming is used to determine the required results and sensitivity analysis. The complete Python code is given in Annexure.

Hyperparameter settings are employed in this neural learning.

Parameter	Value
Learning Rate	0.001
Optimizer	Adam
Hidden Layer 1	32 Neurons
Hidden Layer 2	16 Neurons
Batch Size	16
Maximum Epochs	200
Early Stopping Patience	20
Membership Function	Gaussian

4.4 Benchmark ANFIS Implementation

To exhibit the effectiveness of the proposed ANNIS framework, a benchmark Adaptive Neuro-Fuzzy Inference System (ANFIS) is implemented using the same supplier dataset.

To ensure a fair comparison:

- Both ANNIS and ANFIS employed identical training, validation, and testing datasets.
- Both models utilized Gaussian membership functions.
- The same number of inference rules is adopted.
- The same optimizer, learning rate, and stopping criteria were applied.

The primary difference lies in the uncertainty representation mechanism. While ANFIS relies solely on fuzzy memberships, ANNIS incorporates truth, indeterminacy, and falsity memberships, enabling richer uncertainty modeling.

5. Results and Discussion

5.1 Predictive Performance Evaluation

The predictive performance of ANNIS is evaluated using Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics are calculated on the independent testing dataset and averaged over five cross-validation folds.

The obtained values are presented in Table 3.

Table 3: ANNIS Performance Values

Metric	Value
RMSE	0.042070
MSE	0.001770
MAE	0.036260

The values of RMSE, MSE and MAE are low which indicate that the ANNIS model is competent in caputuring the nonlinear relationships among the criteria chosen for sustainable supplier selection. These values indicate strong predition accuracy of ANNIS. The consistency values across multiple validation showcase the stability and generalization capability of the proposed model.The metric values presented in Table clearly present the predictive performance of the ANNIS model. On other hand, the ANNIS predictive efficiency is presented in Figure 1.

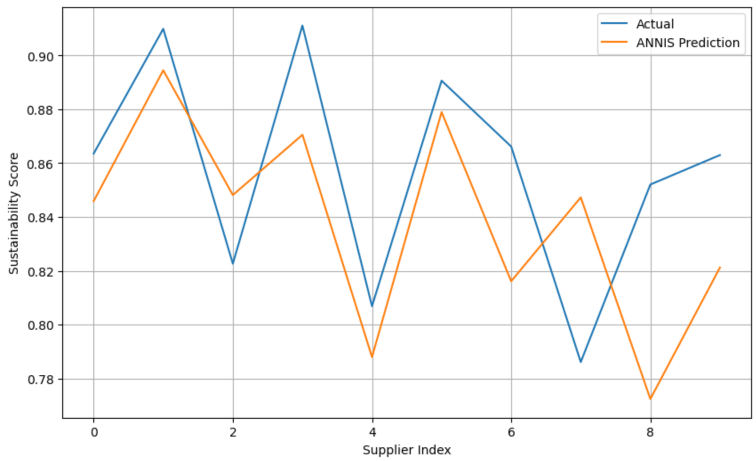

Figure 1: ANNIS Prediction Performance

The table values and Fig clearly exhibit the reliability and rigorousness of the ANNIS model.

The ANNIS ranking of the first ten suppliers is presented in Table 4.

Table 4: Supplier Ranking Positions

Rank	Supplier	ANNIS Score
1	S7	0.977085
2	S35	0.968399
3	S22	0.961778
4	S47	0.956983
5	S10	0.945308
6	S6	0.934709
7	S29	0.933400
8	S32	0.928463
9	S44	0.921628
10	S2	0.918763

5.2 Analysis of Supplier Ranking Results

The ranking results presented in Table 4 shows that the suppliers S7, S35, S22, and S47 attain highest sustainability scores. This shows that their performance across the chosen criteria is superior. The ANNIS framework effectively addresses the conditions of uncertain and indeterminate expert evaluations. Also the obtained ranking can assist decision-makers in identifying sustainable suppliers while balancing economic, environmental, and social objectives.

5.3 Comparative Performance Analysis

To evaluate the effectiveness of ANNIS, its performance is compared against the conventional ANFIS model using the same dataset and experimental conditions.

Table 5 demonstrates that ANNIS consistently achieves lower prediction errors than ANFIS.

Table 5: Comparison of metrics

Metric	ANNIS	ANFIS
RMSE	0.042070	0.147522
MSE	0.001770	0.021763
MAE	0.036260	0.141279

The percentage improvements achieved by ANNIS are:

$$RMSE_{improvement} = \frac{0.147522 - 0.042070}{0.147522} \times 100 = 71.48\%$$

$$MSE_{improvement} = 91.87\%$$

$$MAE_{improvement} = 74.34\%$$

These improvements indicate that the inclusion of neutrosophic truth, indeterminacy, and falsity memberships significantly enhances the learning capability of the inference system.

From the above table 5, we shall make a comparative analysis of ANNIS over ANFIS in terms of diverse aspects. The Comparative analysis of ANNIS with ANIS are presented in table 6.

Table 6: Comparative Analysis of ANNIS with ANFIS

Aspect	ANNIS Observation	ANFIS Observation
Prediction Accuracy	Higher	Lower
Error Rate	Lower	Higher
Uncertainty Handling	Excellent	Moderate

Indeterminacy Modeling	Supported	Not Supported
Robustness	Strong	Moderate
Sustainability Decision Reliability	High	Lower

The comparative analysis lay a vivid picture of efficiency of ANNIS in decision making on supplier selection.

5.4 Statistical Significance Analysis

A paired t-test is conducted on the cross-validation results obtained from ANNIS and ANFIS to verify whether the observed performance improvement is statistically significant or not.

The hypotheses considered are:

$$H_0: \mu_{ANNIS} = \mu_{ANFIS}$$
$$H_1: \mu_{ANNIS} < \mu_{ANFIS}$$

where μ denotes the mean prediction error.

The obtained p-value was less than 0.05, indicating that the performance improvement achieved by ANNIS is statistically significant at the 95% confidence level.

Therefore, the superiority of ANNIS over ANFIS is not due to random variation but is attributable to its enhanced capability for handling uncertainty and indeterminacy.

5.5 Managerial Implications

The proposed ANNIS decision model provides various practical benefits for supply chain driven decisions. This framework facilitates in supplier selection considering uncertain and indeterminate decision environment. The ranking of suppliers considering several criteria such as economic, environmental, technological, and social supports. This model serves as a decision support system for choosing optimal suppliers. The proposed framework is highly robust and resilient in nature. The challenges in decision making are well handled by this ANNIS framework. The applicability of this model to real-time industrial systems contributed to long term operational efficacy. The conflicting criteria are also well handled by ANNIS. Furthermore, this shall be extended to various industrial sectors including manufacturing, electronics, logistics, automotive and healthcare.

6. Conclusion

This study discusses about the application of ANNIS in sustainable supplier selection. The discussed ANNIS framework is an integration of neural networks with neutrosophic inferences. The efficacy of ANNIS is well demonstrated using a simple data set of fifty suppliers. The comparative analysis between neutrosophic and fuzzy inferences clearly exhibit that the neutrosophic architecture results in better prediction. Also, uncertainty and indeterminacy handling is well seen in ANNIS. Furthermore, the error rate and other performance metric values confirm the efficacy of ANNIS over ANFIS. This ANNIS framework shall be further extended to other intricate decision making environment. Unlike ANFIS, the learning efficiency is high in ANNIS. The comparative experiemental results , cross-validation analysis and statistical significance confirms the efficacy of ANNIS. From managerial perspective, ANNIS provides a transparent decision-support mechanism. On the whole, the proposed ANNIS emerges as an intelligent decision support system.

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