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Prediction of Transportation Costs Using Trapezoidal Neutrosophic Fuzzy Analytic Hierarchy Process and Artificial Neural Networks

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ABSTRACT Transportation is one of the critical functions in any business, and its cost depends on many constraints, including driver behavior, weather, distance, and demand in the market. This study proposes a novel approach for multi-criteria decision-making problems using the analytical hierarchy process (AHP) with the trapezoidal neutrosophic fuzzy numbers to produce the best criteria for evaluating total transportation cost. The proposed trapezoidal neutrosophic fuzzy analytical hierarchy process (TNF-AHP) determines the most significant criteria to be considered for further investigation in ANN training. In this study on the transportation problem (TP), the demands at different destination points and the distances between source and demand cities were determined. An artificial neural network (ANN) model has been proposed for the collected data of the TP to investigate the prediction of total transportation cost. The proposed ANN model predicts the total transportation cost with two input which were chosen by the TNF-AHP. Collected data are trained from 2 to 25 neurons with a logsig activation function, and the ideal model for ANN has been observed by Levenberg-Marquardt's feed-forward back-propagation (trainlm) learning algorithm with a single hidden layer (6-9-1) topology. It is found that the ANN model can predict the total transportation cost with high efficiency as the R values indicate a high degree of correlation. The recommended ANN model, mean absolute percentage error, Pearson product-moment correlation coefficient (R), and mean square error have been obtained adequately. The ANN model validation has been conducted, and its results are compared with the collected data.

INDEX TERMS Analytical hierarchy process, artificial neural network, feed forward back propagation learning algorithm, transportation problem, trapezoidal neutrosophic fuzzy number.

I. INTRODUCTION

Transportation cost is one of the costs for any business involving a supply chain. Nowadays, determining the total transportation cost gets challenging as the different transportation constraints are not easy to accumulate in conventional mathematical modeling. We consider transportation costs based on supply, demand, and conveyance constraints, but it has been noted that the transportation cost also changes with the condition of roads. There may be different road surfaces on routes between source and destination. Also, sometimes the driver has to pay donations to some local people in the festive season, and toll taxes are taken for each vehicle. It varies for routes and vehicle types. Hence, per unit transportation cost is not easy to calculate, and fixed charges also vary. Thus, in such a situation, where unit transportation cost and other transportation conditions are uncertain, mathematical models for the total transportation cost are not acceptable because it requires additional assumptions. Since there are many constraints/criteria, such as demand, weather, distance, driver behavior, etc., in the transportation problem, decision-makers (DMs) have to select the best criteria for evaluating the total transportation cost. Transportation is strongly linked with shipping commodities from different sources to destinations.

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Incredibly many numbers of substantial applications can be formulated as a transportation problem (TP). Hitchcock [1] termed TP as a particular case of the Linear Programming Problem (LPP). TP aims to decide the transportation rule that minimizes the total transportation cost. In the classical models of TP, there are many input parameters, namely unit transportation cost, availability of goods at source and demands of goods at destinations, etc. TP is further developed into a solid transportation problem (STP) considering the capacities of conveyances [2].

Recently, TP has achieved more attention from researchers for modeling in both certain and uncertain environments. Recently, most researchers focused on TP/STP in different environments such as fuzzy, rough interval, etc.

In TP, some fixed costs are charged for different reasons, such as tax for interstate border crossing, road permit fees, toll charges, etc. This extra cost is also considered in the total transportation cost. Over the years, there have been numerous researchers presented many papers in this area considering the different environments such as fuzzy, type-2 fuzzy, etc. [3], [4]. Baidya *et al.* [5] use the gradient reduced method and genetic algorithm to solve the traditional TP. In recent years, STP has been acknowledged enough with abundant models and algorithms [6]–[8] under uncertain environments. Determining transportation costs is not an easy task for the DM. DM is not always equipped to handle all the constraints, and they do not consider the linguistic constraints such as driver behavior and weather etc. Decision-making for selecting the best criteria is key to successful management. Due to various types of uncertainties, choosing the right decision is not an easy task.

For a large number of DMs, the possible values of linguistic variables cannot be precisely known. There are fuzzy and stochastic methods is available to convey the uncertainties. In this study, such type of uncertainty is expressed by fuzzy numbers such as the neutrosophic fuzzy numbers.

Zadeh [9] proposed fuzzy sets (FS) to overcome difficulties for decision-makers, where the data are inaccurate or uncertain and are represented with the degree of membership between 0 and 1. Atanasov [10] conceptualized the intuitionistic fuzzy set (IFS), where it was challenging to underline the membership degree using a specific value, and proposed a method to overcome the lack of insight of non-membership degrees. FS theory has been advanced and generalized in terms of IFS, and it cannot still handle other types of uncertainties, such as inconsistent and indeterminate information. Suppose if any statement is said to be true, the possibility of whether the statement is really true is 0.5; if it is said to be false, the possibility is 0.6, and for it is said not to be sure, the possibility is 0.2. Such types of problems are beyond the capacity of FS and IFS, and hence new theories are needed.

Therefore, Smarandache [11] suggested the concept of neutrosophic sets (NS), and later Rivieccio [12] indicates that NS is a set where each element of the universe has a degree of truth, indeterminacy, and falsity, and it lies between [0, 1]. However, NS is tough to implement in real-life problems without explicit details. Hence the extension of NS has been proposed as a single-valued neutrosophic set (SVNS) [13], [14]. Ye [15] proposed combining trapezoidal fuzzy numbers with a single-valued neutrosophic set to introduce trapezoidal neutrosophic fuzzy numbers (TNFN).

Concerning the selection of best criteria, a novel multi-criteria decision-making (MCDM) approach is proposed. The AHP with the trapezoidal neutrosophic fuzzy numbers is proposed in this paper.

The AHP, introduced by Wind and Saaty [16], is an effective technique extensively practiced in modeling the human intelligence mechanism. AHP allows decision-makers to organize a complicated problem in a hierarchical structure of its components according to the rank of management levels. It apprehends the choices of DMs over a set of the relation of relevant criteria. AHP minimizes the risk of inconsistency.

Bellman and Zadeh [17] applied the concept of FS and considered it as a crucial tool for determining the MCDM problems. Yager [18], observes that FS is one of the most powerful aspects to represent multi-objective decision problems having uncertainty. Nowadays IFS is widely used in MCDM problems [19]–[21]. Chen *et al.* [22] solved the MCDM problems by proposing interval-valued hesitant fuzzy sets. Peng [23], with hesitant interval-valued intuitionistic fuzzy sets, introduced an MCDM approach. Zhang *et al.* [24] developed an MCDM in an interval neutrosophic environment based on aggregation operators. Sarma *et al.* [25] show that the TNFN provides a better solution in comparison to the trapezoidal fuzzy numbers. Based on the literature reviews, it is found that no researcher has proposed AHP with the trapezoidal neutrosophic fuzzy numbers.

In contrast, the artificial intelligence (AI) model minimizes the cost, time, and complexity to solve TP considerably. AI is the curriculum that follows to explore natural intelligence and build intelligent systems. The vast scope of AI includes classification, pattern recognition, identification, goal tracking, data inversion, adaptive filtering, estimation, modelling, and prediction, etc. [26]–[29], [30]–[33]. Gonzalez *et al.* [34] presented artificial intelligence image processing and thermal imaging system with a crewless aerial vehicle to monitor wildlife in their natural habitat. Awad and Janson [35] develop a prediction model for tuck accidents in a transportation problem using AI and regression techniques.

The neural network is one of the most well-known techniques in AI. Nowadays, researchers have used ANN tools in inspecting input-output paradigms to avoid lengthy and rigorous experiments to predict the output efficiently and quickly. Kirby and Parker [36] reviewed ANN practices in science, engineering, psychology, and management and developed one of the key AI technologies to overcome the transport problem. Inspired by biological systems, especially by research into the human brain, ANN is fit to assimilate and conclude from experiences. According to Widrow *et al.* [37], ANNs are frequently used for an extensive range of tasks in different fields of business, industry, and science. One major application area of ANN is forecasting [38]. According to

Ismail *et al.* [39], Lavenberg-Marquardt's back-propagation learning algorithm has faster and excellent convergence among different other types of learning algorithms. Gazder and Ratrout [40] investigated a logit-ANN for mode selection model and used it in a case study for border transportation. Bilegan *et al.* [41], predicted a freight demand for intermodal terminals using the neural network. Kumar *et al.* [42] presented a neural network-based model for short-time prediction of traffic volume in non-urban highways under heterogeneous conditions, and they concluded that the ANN model was capable of forecasting vehicle counts precisely.

Zhang *et al.* [43] compiled published research in AI and discussed ANN modeling issues and the future research directions in AI. Wang *et al.* [44] described a method for determining the topology of multilayer feed-forward neural networks. Ismail *et al.* [39] have given that the training algorithm, trainlm, has good convergence. Siqueira [45] presented a procedure that uses Wang's recurrent neural networks to solve the transportation problem. Some literature reviews of AI techniques in the different subject areas of TP are presented in Table 1.

ANN has several distinguishing features that make them beneficial and interesting for a predicting task. ANNs can learn from training sample data set and hence requires minimum programming. The noise tolerance of ANNs is high so that they have less difficulty with situations compare to normal symbolic systems. ANN techniques are also related to the decision-making process under uncertainty [46]. The conventional model-based techniques require many assumptions, but ANN is a data-driven flexible method that requires a few prior assumptions. The intrinsic versatile qualities of ANN make them a suitable method for those problems whose solutions need knowledge that is not easy to identify but for which there are much data or information that can be obtained.

In the literature, there are several papers in TP using AI techniques to address different issues such as driver behavior, pavement maintenance, vehicle classification, traffic control, etc. But to the best of our knowledge, no researcher might have considered forecasting transportation costs for TPs. Many researchers work on the modeling of TP/STP in fuzzy or type-2 fuzzy approaches to address the uncertain environments in the literature. But none of the researchers investigated TP with an ANN prediction.

TP is a problem where the solution requires ample knowledge about the input parameters, constraints, and various solution techniques. When transportation occurs, it compels many constraints, and formulating the mathematical model for all constraints is usually challenging. For this reason, selecting the best constraints is one of the most critical issues, and it is one of the significant contributions of our study. Therefore, we have focused on the issues selecting constraints to predict total transportation cost through ANN modeling. ANN is applied for a real-life case study explained in Section VI. In this study, the following pieces of information are needed to predict the transportation cost.

- Past information about amounts of goods demanded at different destinations.
- Distance between source and demand points.
- Information on the previous total transportation cost.

This study aims to propose a novel TNF-AHP technique to choose the best criteria for TP and an ANN model to predict the total transportation cost of the TP. The study helps DM to focus on the important criteria in planning transportation and to predict the transportation cost, given the distances between source and destinations and the demands at destinations. Also, the proposed study for the determination of transportation cost is illustrated with an empirical case study to show the effectiveness of the proposed methods.

Based on the above literature review, the following objectives have been drawn:

- To propose a new, efficient, and straightforward AHP using TNFN for MCDM problems.
- To evaluate the feasibility of ANN as a reliable structure to predict the expected total transportation cost.
- To propose an ANN model for the accurate prediction of transportation input and output parameters.
- To investigate the total transportation cost of TP based on prior data or observations.

The remainder of this paper is organized into nine sections: Section II provides some basic information on neutrosophic fuzzy numbers and mathematical operations on the trapezoidal neutrosophic fuzzy numbers. Section III describes the steps of the proposed TNF-AHP. Section IV discusses the application of TNF-AHP with a case study. The case study is described with the collected data in Section V. In Section VI, some outline and flow chart of solution procedure is presented. In Section VII, the ANN modeling is provided for the proposed TP. Results are discussed in Section VIII with some managerial insights and limitations of the proposed research are addressed. Lastly, some conclusions and future research are presented in Section IX.

II. PRELIMINARIES

This section provides the basic definitions of neutrosophic sets, single-valued neutrosophic sets, trapezoidal neutrosophic numbers and explains the various operations on trapezoidal neutrosophic numbers.

Definition 1: [62] Let X be a space of points, $x \in X$. A neutrosophic set β in X is defined by a truth membership function $T_\beta(x)$, an indeterminacy membership function $I_\beta(x)$, and a falsity membership function $F_\beta(x)$. $T_\beta(x)$, $I_\beta(x)$, and $F_\beta(x)$ are real and subsets of [0,1] i.e., $T_\beta(x) : X \longrightarrow [0, 1]$, $I_\beta(x) : X \longrightarrow [0, 1]$, $F_\beta(x) : X \longrightarrow [0, 1]$. Also, the sum of $T_\beta(x)$, $I_\beta(x)$, and $F_\beta(x)$ is $0 \leq T_\beta(x) + I_\beta(x) + F_\beta(x) \leq 3$.

Definition 2: Assume a universe of discourse is X. A single-valued neutrosophic set β over X taking the form as in [62] $\beta=\{\langle x, T_\beta(x), I_\beta(x), F_\beta(x) : x \in X\rangle\}$, where $T_\beta(x) : X \longrightarrow [0, 1]$, $I_\beta(x) : X \longrightarrow [0, 1]$, $F_\beta(x) : X \longrightarrow [0, 1]$ and $0 \leq T_\beta(x) + I_\beta(x) + F_\beta(x) \leq 3 \quad \forall x \in X$. $T_\beta(x)$, $I_\beta(x)$,

TABLE 1. Previous works in TP using AI techniques.

Author's name	Subject area
Zhengping et al. [47]	Driver behavior
Kikuchi et al. [48]	Origin-destination parameter estimation
Pozarycki et al. [49]	Pavement maintenance
Bielli et al. [50]	Traffic Control
Bhattacharya [51]	Driver behavior
Kayikci [52]	Freight logistics
Saâdaoui [53]	Air traffic management
George et al. [54]	Vehicle classification
Lin et al. [55]	Travel time in transportation forecasting
Mazarakis and Avaritsiotis [56]	Vehicle classification
Kirby and Parker [36]	Traffic pattern analysis
Swiderski et al. [57]	Freight operations
Ghanim and Lebdeh [58]	Traffic forecasting
Salido et al. [59]	Maritime transport
Lu et al. [60]	Traffic control
Xiao et al. [61]	Air transport
This study	**Transportation cost forecasting**

$F_\beta(x)$ are the degrees of truth membership, indeterminacy membership, and false membership of x to β, respectively.

Definition 3 [62]: The single-valued trapezoidal neutrosophic numbers $\widetilde{\beta}$ denoted by $\langle(a_1, a_2, a_3, a_4), T_\beta, I_\beta, F_\beta\rangle$ are neutrosophic set in R with the truth membership, indeterminacy membership and falsity membership functions are defined below:

$$T_\beta(x) = \begin{cases} \alpha_{\widetilde{\beta}}(\dfrac{x-a_1}{a_2-a_1}) & \text{if } a_1 \le x \le a_2 \\ \alpha_{\widetilde{\beta}} & \text{if } a_2 \le x \le a_3 \\ \alpha_{\widetilde{\beta}}(\dfrac{a_4-x}{a_4-a_3}) & \text{if } a_3 \le x \le a_4 \\ 0 & \text{otherwise} \end{cases}$$

$$I_\beta(x) = \begin{cases} \dfrac{(a_2-x+\theta_{\widetilde{\beta}}(x-a_1))}{a_2-a_1} & \text{if } a_1 \le x \le a_2 \\ \theta_{\widetilde{\beta}} & \text{if } a_2 \le x \le a_3 \\ \dfrac{(x-a_3+\theta_{\widetilde{\beta}}(a_4-x))}{a_4-a_3} & \text{if } a_3 \le x \le a_4 \\ 1 & \text{otherwise} \end{cases}$$

$$F_\beta(x) = \begin{cases} \dfrac{(a_2-x+\gamma_{\widetilde{\beta}}(x-a_1))}{a_2-a_1} & \text{if } a_1 \le x \le a_2 \\ \gamma_{\widetilde{\beta}} & \text{if } a_2 \le x \le a_3 \\ \dfrac{(x-a_3+\gamma_{\widetilde{\beta}}(a_4-x))}{a_4-a_3} & \text{if } a_3 \le x \le a_4 \\ 1 & \text{otherwise} \end{cases}$$

where $\alpha_{\widetilde{\beta}}, \theta_{\widetilde{\beta}}$, and $\gamma_{\widetilde{\beta}}$ are the maximum degree of truth membership, the minimum degree of indeterminacy membership, and the minimum degree of falsity membership, respectively. $\alpha_{\widetilde{\beta}}, \theta_{\widetilde{\beta}}$ and $\gamma_{\widetilde{\beta}} \in [0,1]$.

Definition 4: [63] Let $\hat{a}=\langle(a_1, a_2, a_3, a_4), \alpha_{\widetilde{a}}, \theta_{\widetilde{a}}, \gamma_{\widetilde{a}}\rangle$ and $\hat{b}=\langle(b_1, b_2, b_3, b_4), \alpha_{\widetilde{b}}, \theta_{\widetilde{b}}, \gamma_{\widetilde{b}}\rangle$ are the two single-valued trapezoidal neutrosophic number, and $\Upsilon \ge 0$ be any real number. Then:

1. The addition of two trapezoidal neutrosophic numbers is defined as:

$\hat{a}+\hat{b}= \langle(a_1+b_1, a_2+b_2, a_3+b_3, a_4+b_4), \alpha_{\widetilde{a}}+\alpha_{\widetilde{b}}-\alpha_{\widetilde{a}}*\alpha_{\widetilde{b}}, \theta_{\widetilde{a}}*\theta_{\widetilde{b}}, \gamma_{\widetilde{a}}*\gamma_{\widetilde{b}}\rangle$

2. The multiplication of two trapezoidal neutrosophic numbers is defined as:

$\hat{a}*\hat{b} =\langle(a_1b_1, a_2b_2, a_3b_3, a_4b_4), \alpha_{\widetilde{a}}*\alpha_{\widetilde{b}}, \theta_{\widetilde{a}}+\theta_{\widetilde{b}}-\theta_{\widetilde{a}}*\theta_{\widetilde{b}}, \gamma_{\widetilde{a}}+\gamma_{\widetilde{b}}-\gamma_{\widetilde{a}}*\gamma_{\widetilde{b}}\rangle$

3. The multiplication of trapezoidal neutrosophic numbers by constant value is defined as:

$\Upsilon\hat{a}=\langle(\Upsilon a_1, \Upsilon a_2, \Upsilon a_3, \Upsilon a_4), (1-(1-\alpha_{\widetilde{a}}))^\Upsilon, (\theta_{\widetilde{a}})^\Upsilon, (\gamma_{\widetilde{a}})^\Upsilon\rangle$.

4. $\hat{a}^\Upsilon$ is defined as:

$\hat{a}^\Upsilon=\langle(a_1^\Upsilon, a_2^\Upsilon, a_3^\Upsilon, a_4^\Upsilon), (\alpha_{\widetilde{a}})^\Upsilon, (1-(1-\theta_{\widetilde{a}}))^\Upsilon, (1-(1-\gamma_{\widetilde{a}}))^\Upsilon\rangle$.

where $\alpha_{\widetilde{a}}, \theta_{\widetilde{a}}, and \gamma_{\widetilde{a}}$ are the truth, indeterminacy, and falsity function, respectively for the single-valued neutrosophic number â, whereas $\alpha_{\widetilde{b}}, \theta_{\widetilde{b}}, and \gamma_{\widetilde{b}}$ are the truth, indeterminacy, and falsity function, respectively for the single-valued neutrosophic number $\hat{b}$.

Definition 5 [62] (The inverse of trapezoidal neutrosophic number):

Let $\hat{a} = \langle(a_1, a_2, a_3, a_4), \alpha_{\widetilde{a}}, \theta_{\widetilde{a}}, \gamma_{\widetilde{a}}\rangle$ is the single-valued trapezoidal neutrosophic number, then

$$\hat{a}-1 = \langle(\frac{1}{a_4}, \frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}), \alpha_{\widetilde{a}}, \theta_{\widetilde{a}}, \gamma_{\widetilde{a}}\rangle \quad \text{where } \hat{a} \neq 0$$

where $\alpha_{\widetilde{a}}, \theta_{\widetilde{a}}, and \gamma_{\widetilde{a}}$ are the truth, indeterminacy, and falsity function, respectively.

III. PROPOSED TRAPEZOIDAL NEUTROSOPHIC FUZZY ANALYTICAL HIERARCHY PROCESS (TNF-AHP)

This section proposes a novel approach for multi-criteria decision-making (MCDM) based on the trapezoidal neutrosophic fuzzy numbers and presents the steps of the proposed methodology.

The TNF-AHP incorporates the fuzzy logic into the traditional AHP since it does not include uncertainty for individual reasoning. Fuzzy logic involves the use of linguistic variables.

TABLE 2. Linguistic terms with the trapezoidal neutrosophic fuzzy numbers.

Satty scale	Linguistic terms	Trapezoidal neutrosophic fuzzy number
1	Equally important (E. Imp.)	$\langle (1,1,1,1)1,0,0\rangle$
3	Weakly important (W. Imp.)	$\langle (2,3,4,5)0.85,0.45,0.15\rangle$
5	Fairly important (F. Imp.)	$\langle (4,5,6,7)0.8,0.5,0.3\rangle$
7	Strongly important (S.Imp.)	$\langle (6,7,8,9)0.9,0.5,0.1\rangle$
9	Absolutely important (A. Imp.)	$\langle (9,9,9,9)0.8,0.4,0.2\rangle$
2	The intermittent value between two adjacent scales	$\langle (1,1,2,3)0.8,0.4,0.2\rangle$
4		$\langle (2,3,4,5)0.9,0.5,0.3\rangle$
6		$\langle (4,5,6,7)0.7,0.5,0.4\rangle$
8		$\langle (6,7,8,9)0.6,0.3,0.1\rangle$

A linguistic variable is a variable whose values are words rather than numbers. Here, the proposed AHP uses TNF logic which provides the knowledge of truth, indeterminacy, and falsity of any linguistic variable. Hence, the convergence of AHP is enhanced by improving the fuzzy logic approaches. In TNF-AHP, the pairwise comparisons for criteria have been obtained through the linguistic variables expressed by TNFN and explained in Table 2.

The proposed TNF-AHP methodology contains the following steps:

[Step 1.] Compare the criteria with linguistic terms are given in Table 2.

$$A^k = \begin{bmatrix} c_{11}^k & c_{12}^k & \dots & c_{1n}^k \\ c_{21}^k & c_{22}^k & \dots & c_{2n}^k \\ \dots & \dots & \dots & \dots \\ c_{n1}^k & c_{n2}^k & \dots & c_{nn}^k \end{bmatrix} \tag{1}$$

[Step 2.] If there is more than one decision-maker, the preferences of each decision-maker (c_{ij}^k) are averaged and (c_{ij}) is calculated as in the Equation (2).

$$c_{ij} = \frac{\sum_{k=1}^{K} c_{ij}^k}{K} \tag{2}$$

[Step 3.] According to averaged preferences, the pairwise contribution matrix is updated as shown in Equation (3).

$$A = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & c_{22} & \dots & c_{2n} \\ \dots & \dots & \dots & \dots \\ c_{n1} & c_{n2} & \dots & c_{nn} \end{bmatrix} \tag{3}$$

[Step 4.] Now, the geometric mean of fuzzy comparison values of each criterion is calculated as shown in Equation (4). Here, s_i represents a trapezoidal neutrosophic fuzzy number.

$$s_i = \left\{ \prod_{j=1}^{n} c_{ij} \right\}^{\frac{1}{n}}, \quad i = 1, 2 \dots\dots n \tag{4}$$

[Step 5.] Now, the fuzzy weight for each criterion can be found by the following three sub-steps and using Equation (5).
[Step 5a.] Find the vector addition of each s_i.
[Step 5b.]Find the (-1) power of summation vector, and arrange the trapezoidal neutrosophic number with the knowledge of the inverse of the trapezoidal neutrosophic number discussed in Section II.
[Step 5c.] To get the weight of each criterion i (w_i), multiply each s_i with the reverse vector obtained in the above step.

$$\begin{aligned} w_i &= s_i \otimes (s_1 \oplus s_2 \oplus s_3 \oplus \dots . \oplus s_n)^{-1} \\ &= \langle (lw_i, mw_i, uw_i, vw_i), T_\beta, I_\beta, F_\beta \rangle \end{aligned} \tag{5}$$

[Step 6.] Since w_i are a trapezoidal neutrosophic number, it is defuzzified using the ranking method proposed by Abdel-Baset *et al.* [62]. The conversion of the trapezoidal neutrosophic number into a crisp form is given below.

a. If the problem is maximization type, use the mathematical formula given in Equation (6).

$$R(w_i) = \left(\frac{lw_i + 2(mw_i + uw_i) + vw_i}{2}\right) + (T_\beta - I_\beta - F_\beta) \tag{6}$$

b. If the problem is minimization type, use the mathematical formula given in Equation (7).

$$R(w_i) = \left(\frac{lw_i - 3(mw_i + uw_i) + vw_i}{2}\right) + (T_\beta - I_\beta - F_\beta) \tag{7}$$

Here, the function is maximization type, so consider Equation (6) to defuzzified the trapezoidal neutrosophic number.

[Step 7.] Finally, $R(w_i)$ is averaged with the help of Equation (8).

$$w_i = \frac{R(w_i)}{\sum_{i=1}^{n} R(w_i)} \tag{8}$$

Through these 7 steps, one can find the weight w_i for criteria. Finally, the criteria with maximum weight are advised to DMs.

TABLE 3. Pairwise comparison.

Sl.No	A.Imp	S.Imp.	F.Imp.	W.Imp.	Criteria	Eq.Imp.	Criteria	W.Imp.	F.Imp.	S.Imp.	A.Imp
1					Driver Behavior		Demand				✓
2					Driver Behavior		Distance			✓	
3		✓			Driver Behavior		Weather				
4					Demand	✓	Distance				
5	✓				Demand		weather				
6		✓			Distance		weather				

TABLE 4. Comparison matrix in trapezoidal neutrosophic fuzzy numbers.

Criteria	Driver behavior	Demand	Distance	Weather
Driver behavior	$\langle(1,1,1,1)1,0,0\rangle$	$\langle(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{9})0.8,0.4,0.2\rangle$	$\langle(\frac{1}{9},\frac{1}{8},\frac{1}{7},\frac{1}{6})0.9,0.5,0.1\rangle$	$\langle(2,3,4,5)0.85,0.45,0.15\rangle$
Demand	$\langle(9,9,9,9)0.8,0.4,0.2\rangle$	$\langle(1,1,1,1)1,0,0\rangle$	$\langle(1,1,1,1)1,0,0\rangle$	$\langle(9,9,9,9)0.8,0.4,0.2\rangle$
Distance	$\langle(6,7,8,9)0.9,0.5,0.1\rangle$	$\langle(1,1,1,1)1,0,0\rangle$	$\langle(1,1,1,1)1,0,0\rangle$	$\langle(6,7,8,9)0.9,0.5,0.1\rangle$
Weather	$\langle(\frac{1}{5},\frac{1}{4},\frac{1}{3},\frac{1}{2})0.85,0.45,0.15\rangle$	$\langle(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{9})0.8,0.4,0.2\rangle$	$\langle(\frac{1}{9},\frac{1}{8},\frac{1}{7},\frac{1}{6})0.9,0.5,0.1\rangle$	$\langle(1,1,1,1)1,0,0\rangle$

Similarly for those study which has more than one alternatives to choose, the same steps is followed to choose the best alternatives and every alternative score is determined by multiplying each alternative weight with associated criteria. Also, the alternative with the largest score is advised to the DMs.

This study considers single alternatives as total transportation cost. Hence, only determination of criteria is shown.

IV. APPLICATION OF TNF-AHP IN PROPOSED CASE STUDY

The proposed TNF-AHP is applied to a case study to determine the two best criteria for the ANN training in predicting transportation cost among four criteria identified through the interview with the production manager in a company. The four criteria tested with TNF-AHP in this case study are driver behavior, demand, distance, and weather. The following subsections discusses the procedure for obtaining the two best criteria with TNF-AHP.

A. DETERMINING BEST CRITERIA

An interview was conducted with the production manager to determine the best criteria and assess the total transportation cost. Affirming with his preferences, the pairwise comparison of the criteria is given in Table 3.

From Table 3, a pairwise comparison matrix for the criteria with trapezoidal neutrosophic numbers is obtained in Table 4.

Then, the geometric mean of the trapezoidal neutrosophic fuzzy number of every criterion is determined using Equation (4). Finally, as an example for the driver behavior criteria, the s_1 geometric mean of trapezoidal neutrosophic fuzzy numbers of comparison value is determined in Equation (9).

$$
\begin{aligned}
s_i = \left\{\prod_{j=1}^{n} c_{ij}\right\}^{\frac{1}{n}} &= [\langle(1, 1, 1, 1)1, 0, 0\rangle \\
&* \langle(\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{9})0.8, 0.4, 0.2\rangle \\
&* \langle(\frac{1}{9}, \frac{1}{8}, \frac{1}{7}, \frac{1}{6})0.9, 0.5, 0.1\rangle \\
&* \langle(2, 3, 4, 5)0.85, 0.45, 0.15\rangle]^{\frac{1}{4}} \\
&= \langle(0.416, 0.447, 0.472, 0.494)0.884, 0.363, 0.116\rangle
\end{aligned} \tag{9}
$$

The geometric mean of trapezoidal neutrosophic fuzzy numbers from the comparison matrix for all criteria is presented in Table 5. Also, the total and negative power of total values are given.

In the next step, the relative weight in the trapezoidal neutrosophic fuzzy numbers for all criteria is calculated using Equation (5) and presented in Table 6. For example, the relative weight in trapezoidal neutrosophic fuzzy number for driver behavior is shown in Equation (10).

$$
\begin{aligned}
w_1 &= \langle(0.416, 0.447, 0.472, 0.494)0.884, 0.363, 0.116\rangle \\
&\quad * \langle(0.147, 0.152, 0.158, 0.165)1, 0.009, 0\rangle \\
&= \langle(0.061, 0.068, 0.075, 0.082)0.884, 0.369, 0.116\rangle
\end{aligned} \tag{10}
$$

In the last step, the relative weight obtained in Table 6 is defuzzified. Here, the aim is to find the maximum weight of the criteria. Hence, Equation (6) has been used for defuzzification and the obtained defuzzified values for all the criteria are listed in Table 7. Finally, by using Equation (8) averaged relative weight has been obtained and given in Table 8. Based on these results, demand and distance criteria have the best average score. Hence, the demand and distance criteria are the two best criteria for evaluating total transportation costs.

V. CASE STUDY

The numerical data for ANN training is collected from a small plain land city Varanasi, India. It is surrounded by rural cities from three sides and hilly cities from other sides, as shown in Figure 1. The geography of roads from Varanasi to destination cities is divided into three zones. The three zones of corresponding roads are categorized as;

TABLE 5. Geometric mean of criteria in the trapezoidal neutrosophic fuzzy numbers.

Criteria	s_i
Driver behavior	$\langle(0.416, 0.447, 0.472, 0.494)0.884, 0.363, 0.116\rangle$
Demand	$\langle(3, 3, 3, 3)0.894, 0.225, 0.105\rangle$
Distance	$\langle(2.449, 2.645, 2.828, 3)0.948, 0.293, 0.051\rangle$
Weather	$\langle(0.211, 0.234, 0.265, 0.308)0.884, 0.363, 0.12\rangle$
Total	$\langle(6.076, 6.326, 6.565, 6.802)1, 0.009, 0\rangle$
(-1 power of total)	$\langle(0.147, 0.152, 0.158, 0.165)1, 0.009, 0\rangle$

TABLE 6. Weights of criteria in the trapezoidal neutrosophic fuzzy numbers.

Criteria	Trapezoidal neutrosophic fuzzy weight
Driver behavior	$\langle(0.061, 0.068, 0.075, 0.082)0.884, 0.369, 0.116\rangle$
Demand	$\langle(0.441, 0.456, 0.474, 0.495)0.894, 0.231, 0.105\rangle$
Distance	$\langle(0.36, 0.402, 0.447, 0.495)0.948, 0.299, 0.051\rangle$
Weather	$\langle(0.031, 0.036, 0.042, 0.051)0.884, 0.369, 0.12\rangle$

TABLE 7. Defuzzified weights of criteria.

Criteria	Defuzzified value
Driver behavior	1.226
Demand	1.956
Distance	1.945
Weather	0.518

TABLE 8. Average relative weights of criteria.

Criteria	Average weight
Driver behavior	0.217
Demand	0.347
Distance	0.345
Weather	0.092

- **Zone 1:** - Urban roads containing road links from the factory to markets of Varanasi.
- **Zone 2:** - Rural and urban roads containing road links from the factory to markets in Bhadohi, Chandauli, and Gazipur.
- **Zone 3:** - Plateau, rural and urban roads with parts of the roads having gradients compared to Zones 1 and 2, containing road links from the factory to markets in Mirzapur and Sonbhadra.

Considering the characterization of three zones in mathematical modeling is a rigorous and challenging task. Since the fuel prices change daily, calculating unit transportation costs is not straightforward in a dynamic system.

Therefore, when the DMs have supplied their products for different demands in these three zones simultaneously, the decision-makers face a challenging situation to determine the total transportation cost. Therefore, we consider ANN techniques to predict the total transportation cost.

FIGURE 1. Map of Varanasi.

The following subsection discusses the collection and investigation of data for ANN training and validation.

A. DATA COLLECTION AND INVESTIGATION

Generally, the transportation model is a double constraint model, source and demand constraints, but in this study, we consider the TP as a single constraint TP only addressing the demand constraints. Also, the total transportation cost depends upon the distances between the source and demand points.

To verify the forecasting capabilities of the ANN model, the whole data sample is divided into two samples, i.e., training and test sample. There is no particular method available for the partition of data into the training and test samples.

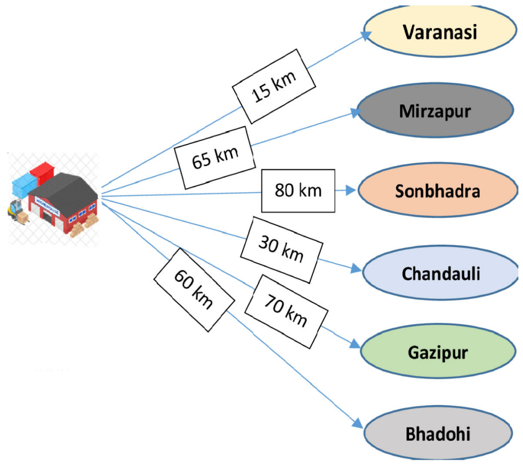

FIGURE 2. **Graphical illustration of TP in a case study.**

The way of selecting the data depends upon the nature of the problem, types of data, and the size of available data. Another issue is the size of the sample. There is no explicit rule to specify the sample size for the given problem. The amount of data for the ANN training relies upon the network structure, the training method, and the complexity of a particular problem or the amount of noise in the data on hand [43]. Using extensive data samples, ANN can be benefited to model any complex structure with greater accuracy.

The requirement for exact total distance and demands is vital for evaluating and verifying ANN models. Here, the distances between source and demand points are crucial determinants of total transportation cost. Therefore, it is necessary to measure the distance correctly.

The procedure for ANN modeling has been applied to real-life data collected from an XYZ flour company (the company name remains confidential by its request) situated in Varanasi, India. The company supplies flour to the neighboring cities of Varanasi. The total transportation cost depends on the amount of quantity transported, distance from the demand cities or points, loading-unloading charges, fixed charges such as toll tax, etc.

For this study, the company provides its past 50 days of data in which they daily supply their flour in three different neighboring cities of Varanasi. Here, the unit of flour is measured in quintal, and the distance of demand cities from Varanasi is measured in kilometer (km). The total transportation cost is given in Indian rupees (INR). The company provides 50 sets of sample data, which we divided into 40 samples for training and 10 samples for testing. The distances to demand cities from the company are given as follows; Varanasi (15 km), Chandauli (30 km), Mirzapur (65 km), Bhadohi (60 km), Gazipur (70 km), and Sonbhadra (80 km).

A graphical illustration of this transportation problem is depicted in Figure 2. In this study, the transportation cost depends upon the number of goods demanded at various destinations or cities, and it also depends upon the distances from the source to different cities where the goods are supplied. The transportation cost increases as the demand amounts and distances increase. The detailed data are given in Table 9:

VI. SOLUTION PROCEDURE

The proposed research aims to forecast the total transportation cost for a particular type of TP using the TNF-AHP and ANN techniques. The solution procedure is in two folds. Firstly, using TNF-AHP, the best criteria/constraints of the TP are selected and secondly, using ANN technique, the total transportation cost is determined with selected criteria. The proposed solution procedures in this case study are explained in detail below.

Step 1. The proposed TNF-AHP has been applied to the case study to find the best criteria.

Step 2. After the best criteria are obtained (demand and distance in this case study), the next step is collecting and arranging the ANN training data.

Step 3. A real-life 50 data sets are collected. Identify the input and output components from the given sample of the data set. If there are any outliers in the sample, remove the outliers from the data set.

Step 4. The above data set normalizes the data between 0.1 to 0.9 using Equation (11), and the first 40 samples are taken for ANN training and the remaining 10 samples for validation.

Step 5. Apply ANN on the above data to accurately forecast the total transportation cost. To successfully implement ANN, ANN is divided into three stages;

5.1. Design Stage: This stage selects the number of the hidden layers, the number of neurons in the hidden layers, and training algorithm. After extensive experiments, a single hidden layer of 9 neurons with trainlm training algorithm is chosen as a suitable ANN model for this study.

5.2. Training Stage: In this stage, a transfer function is selected with exit condition, learning rate, and momentum. A logistic function logsig is used here as a transfer function.

5.3. Generalization Stage: Once the exit condition from training is achieved from the above Training Stage, the validation process starts to validate the training. 70% of data is taken for training purposes from the test sample, and the remaining 30% is used for validation.

Step 6. After the optimal topology for the ANN modeling is obtained, the remaining 10 sample data is used for validation to enhance the validation of the ANN modeling.

Step 7. Obtain the best-predicted values for the total transportation cost.

The overall solution procedure is illustrated as a flow chart in Figure 3.

VII. ANN MODELLING

The ANN model is derived from the biological nervous system. It consists of many neurons and nodes in one or more

TABLE 9. Input values of criteria and the collected transportation cost.

Sl.No.	Demand at different cities (quintal)			Distance of cities (km)			Transportation cost (INR)
	city 1	city 2	city 3	city 1	city 2	city 3	
1	80	75	70	30	70	65	9900
2	85	80	80	15	30	80	9500
3	60	70	70	60	65	70	9900
4	84	90	82	80	70	65	10500
5	75	75	75	60	65	70	8750
6	40	45	65	65	15	60	7200
7	55	54	40	70	60	15	7000
8	48	42	55	60	15	30	7500
9	52	48	64	30	80	65	7750
10	65	58	72	15	30	80	8860
11	85	80	80	80	65	60	9000
12	48	50	50	70	60	30	8000
13	54	59	63	65	30	70	7550
14	60	65	45	30	70	15	7050
15	75	75	58	60	30	70	8800
16	68	72	81	65	80	60	9300
17	60	60	65	80	65	30	8600
18	43	45	49	15	30	65	6250
19	62	68	77	70	60	65	9950
20	77	62	80	65	60	80	9550
21	65	60	55	30	70	15	8250
22	70	80	75	60	15	30	7800
23	50	55	60	65	80	70	6900
24	40	67	48	80	65	60	7000
25	45	45	45	15	30	65	6300
26	60	85	60	30	60	15	6350
27	72	78	84	60	70	80	10500
28	71	66	83	30	15	70	9450
29	65	68	55	65	70	30	7100
30	49	58	60	60	80	65	6900
31	50	60	45	15	30	80	6450
32	65	50	50	70	65	60	7300
33	68	65	80	65	70	15	6950
34	50	63	55	30	80	70	7800
35	60	80	48	60	30	65	8100
36	75	84	65	80	30	15	8450
37	80	87	60	70	15	80	9350
38	48	47	70	15	70	30	7100
39	45	50	67	30	60	65	7700
40	52	70	58	80	65	60	8700
41	65	77	75	60	80	70	10200
42	50	68	45	65	15	30	7150
43	49	50	55	30	60	15	6450
44	78	65	80	15	65	30	7520
45	80	80	64	60	80	70	9650
46	85	80	62	80	70	60	9400
47	42	48	45	65	80	70	6550
48	50	50	42	15	30	60	7150
49	80	85	69	70	65	80	10450
50	68	60	50	30	70	65	8100

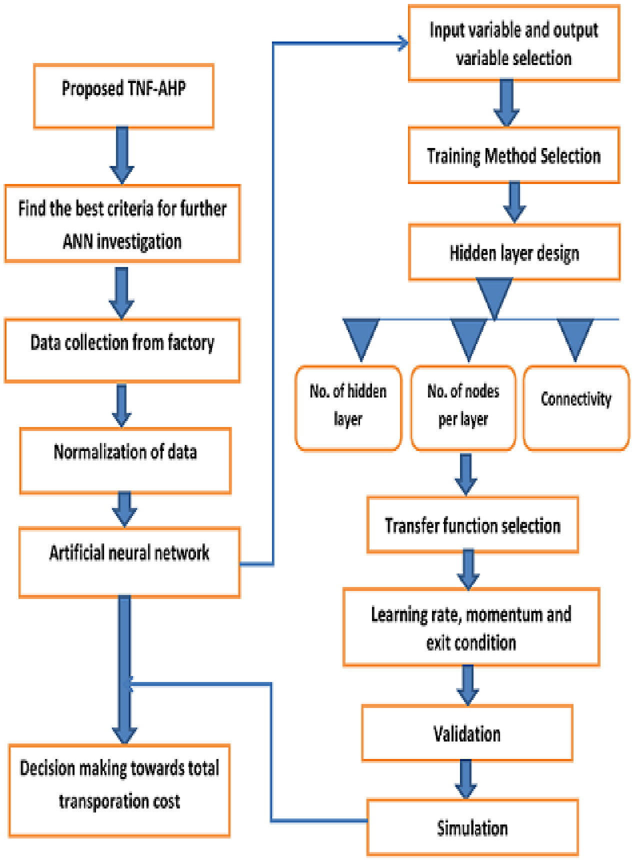

FIGURE 3. **Flow chart of the solution method.**

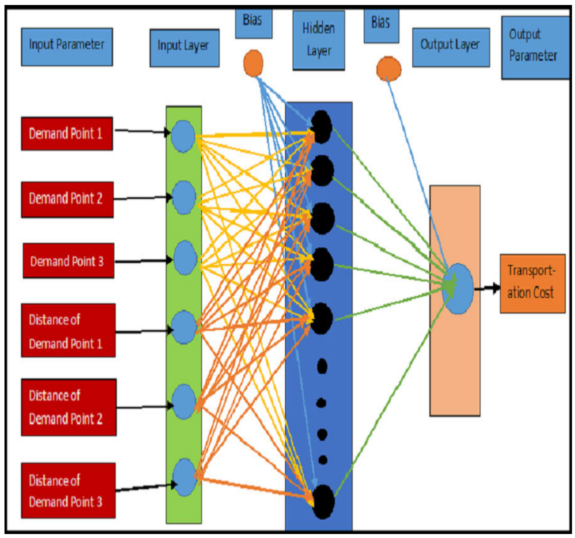

FIGURE 4. **The adopted 6-9-1 ANN model.**

hidden layer(s), firmly interconnected with each other by the linkage weight [64]. The processing of information takes place at numerous elementary elements called neurons. Signals are passed among neurons over connection links. Each connection link has associated weights, which are multiplied by the input signals transmitted in a typical neural network. Each neuron applies an activation function to its net input to determine the output signal. Bias may be considered for a better learning process. ANN has three essential layers; input, hidden, and output layers. The hidden layer may be one or more depends upon the complexity of the problem. ANN models are developed by tuning weights for a set of criteria. These criteria are examined as input and output values. The following process tunes the weights up to the appropriate value to obtain the minimum error between the network output and desired output. Accordingly, training is performed for a sample of input-output data through the ANN model, and when the optimal weights are obtained, the ANN model can predict the output values for those input values that were not covered in the training dataset as well.

Figure 4 shows the general configuration of the ANN model.

Ismail *et al.* [39] proposed that the back-propagation learning algorithm is suitable among many learning algorithms for prediction. The back-propagation algorithm updates weight sets to minimize errors using the gradient descent technique [43].

Trainlm is the network training function and the fastest back-propagation algorithm, which follows Levenberg-Marquardt optimization to update the weight and bais values. Also, logsig is a transfer function that calculates output values from its net input. In this study, the demands of and the distances to three cities have been selected for ANN input layer, while the total transportation cost for the model output layer.

Before the training starts, data should be normalized because non-linear activation functions such as the logistic function generally have the suppressing aspect in reducing the feasible output between [0,1] or [−1,1]. Bhowmik *et al.* [65] used Equation (11) to normalize the data between 0.1 to 0.9.

$$Z_i = 0.1 + \left[\left(\frac{\alpha_i - \alpha_{i_{min}}}{\alpha_{i_{max}} - \alpha_{i_{min}}}\right) \times 0.8\right] \tag{11}$$

where Z_i is the normalized value of α_i and $\alpha_{i_{min}}$ and $\alpha_{i_{max}}$ are the minimum and maximum values in the dataset, respectively.

A. PERFORMANCE EVALUATION OF ANN MODEL

To evaluate the prediction performance, the statistical measures are adopted in this section. Although there are many performance measures for forecasting or regression analysis, the following measures, including Pearson product-moment correlation coefficient (R), mean square error (MSE), mean absolute percentage error (MAPE). The mathematical expression to calculate the R, MSE, and MAPE are given in the following equations [65].

$$R = \sqrt{\left[1 - \left(\frac{\sum_{i=1}^{n}(t^i - o^i)^2}{\sum_{i=1}^{n} o^{i2}}\right)\right]} \tag{12}$$

$$MSE = \left[\frac{\sum_{i=1}^{n}(t^i - o^i)^2}{n}\right] \tag{13}$$

$$MAPE = \left[\sum_{i=1}^{n} \left| \frac{(t^i - o^i)^2}{t^i} \right| \right] \times \frac{100}{n}\% \qquad (14)$$

where n, t^i, and o^i are the total sample size, observed, and predicted values, respectively.

Equation (12) is a Pearson product-moment correlation coefficient used to determine the correlation between observed and predicted values. Equation (13) represents the mean square error to calculate the mean square errors. And Equation (14) is a mean absolute percentage error to measure the model's prediction accuracy. The given ANN model is optimal when $R>0.98$, $MSE<0.001$, and $MAPE< 5\%$ [65].

Through trial-and-error experiments, various numbers of the neurons are tested for achieving optimal network topology for the ANN model The ANN with a single hidden layer and a logsig activation function have been selected for establishing optimal ANN architecture in MATLAB 2016a. Then, a feed-forward back-propagation algorithm has been applied for ANN training.

The first 40 datasets are chosen for training and the last 10 datasets for testing. In the training dataset, 70% of the data has been randomly chosen for training, and 30% of data has been used for validation and testing. The Pearson product-moment correlation coefficient value R and mean square error MSE for 2 to 25 neurons are calculated using Equations (12) and (13), respectively. Also, the average absolute percentage error is calculated by Equation (14). Once the training is completed, and optimal topology is obtained, the remaining data set is applied for the validation. Finally, the normalized data is denormalized with the help of Equation (15).

$$Z_i = 0.1 + \left[\left(\frac{\alpha_{i_{max}} - \alpha_i}{\alpha_{i_{max}} - \alpha_{i_{min}}} \right) \times 0.8 \right] \qquad (15)$$

VIII. RESULT DISCUSSION AND MANAGERIAL INSIGHTS

In this study, selecting the best criteria for the TP is obtained with the proposed TNF-AHP. Among the four criteria of our interests, including driver behavior, demand, distance, and weather, the demand and distance criteria are the best two criteria. Those data are used to predict the total transportation cost using the ANN techniques. The linguistic terms are taken in the trapezoidal neutrosophic fuzzy numbers. The averaged weight for the demand and distance criteria is obtained as 0.347 and 0.345, respectively, in the TNF-AHP analysis. Once the best criteria are obtained, the total transportation cost is predicted from the real-life data in Table 9 by the ANN technique.

The ANN is developed to predict the transportation cost, given the collected transportation data. The trainlm learning algorithm with a single hidden layer has been tested with the logsig activation function. The ANN model runs up to 10000 iterations for 2 to 25 neurons. It has been seen that the maximum R-value and minimum MSE- and MAPE- values are obtained when the hidden layer has 9 neurons. Subsequently, (6-9-1) topology has been established as an optimal topology. The input layer has 6 neurons, the hidden layer has

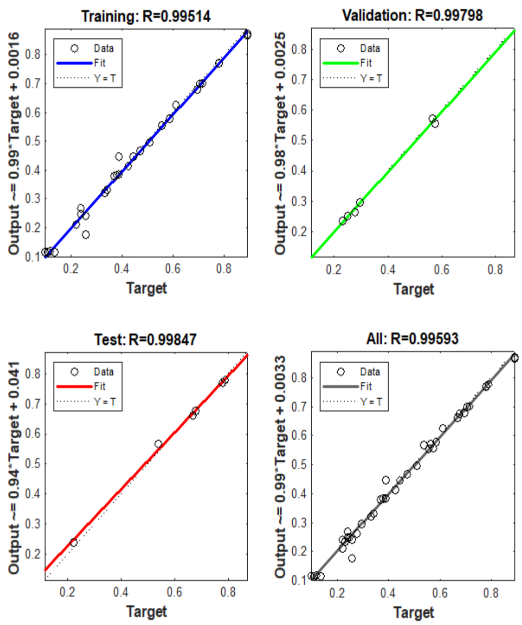

FIGURE 5. R values in the regression analysis on the training values by ANN.

9 neurons, and there is 1 neuron in the output layer. As shown in Figure 5, the training state's regression coefficients are 0.99519, 0.99798, 0.99847, and 0.99593 for training, validation, testing, and overall R values of the established ANN model. From Table 10, it is shown that MSE is high for the small numbers of neurons because the complication arises in the decision due to the lesser number of neurons. The minimum MSE is found at 9 neurons in the hidden layer. Beyond this, as the number of neurons increases, MSE continuously increases. The MSE and MAPE values with the hidden layer of 9 neurons are 0.000421 and 4.34484%, respectively, and it is satisfactory. In contrast, the R-value at 9 neurons is found to be 0.999156, which is the largest. Figure 6 and 7 represent the obtained results of MSE and MAPE for the 2 to 25 number of neurons, respectively.

The variation of R values for 2 to 25 neurons is given in Figure 8. The correlation between predicted transportation cost with collected transportation cost for test cases is given in Figure 9, and the comparison between these two costs is presented in Figure 10.

Once the training was completed for 40 datasets in Table 9, and optimal topology was obtained. The remaining 10 datasets have been tested for the validation purpose with 6-9-1 topology, trainlm learning algorithm, and logsig activation function. In Table 11, the predicted transportation cost and collected transportation cost are given. Also, a comparison between predicted and collected transportation costs is depicted in Figure 11.

A. MANAGERIAL INSIGHTS

This study proposes a way to choose the best criteria for TP from the linguistic terms and an ANN model to estimate the

TABLE 10. Regression analysis and performance measures for different numbers of neurons.

No. of Neurons	Regression Coefficients				Performance Measures		
	Training	Validation	Testing	Overall	MSE	MAPE%	R
2	0.91883	0.99192	0.95334	0.91845	0.008067	21.33887	0.982472
3	0.90021	0.9617	0.97694	0.91409	0.008319	16.62037	0.983379
4	0.9507	0.916	0.93874	0.93415	0.007753	11.04717	0.982281
5	0.99517	0.95657	0.91823	0.96074	0.004527	10.77558	0.991213
6	0.90901	0.94468	0.98721	0.92841	0.006966	16.45277	0.985773
7	0.99126	0.99211	0.99751	0.99246	0.000769	4.837371	0.998486
8	0.98154	0.99585	0.98584	0.98346	0.001664	9.275876	0.996636
9	**0.99514**	**0.99798**	**0.99847**	**0.99593**	**0.000421**	**4.34484**	**0.999156**
10	0.9863	0.91826	0.91581	0.94924	0.002969	8.794887	0.993931
11	0.96006	0.97508	0.96422	0.96506	0.003622	12.3636	0.992659
12	0.9245	0.98133	0.95558	0.93137	0.006742	18.24832	0.985727
13	0.92665	0.95955	0.96849	0.93995	0.006181	16.62144	0.987248
14	0.95017	0.96796	0.94522	0.94445	0.005774	9.316988	0.987346
15	0.97593	0.99735	0.97019	0.97750	0.00226	6.806467	0.995526
16	0.9593	0.99795	0.96274	0.96181	0.003871	7.815438	0.991986
17	0.93525	0.99149	0.99527	0.95281	0.004847	11.03976	0.99067
18	0.94606	0.99763	0.99964	0.96262	0.004321	6.452202	0.991533
19	0.95801	0.94753	0.82792	0.94654	0.005399	12.26091	0.989604
20	0.90968	0.9665	0.99925	0.93156	0.006835	20.39846	0.985667
21	0.93789	0.98145	0.98438	0.94619	0.005858	12.97332	0.989204
22	0.92038	0.96548	0.99269	0.94515	0.00539	15.25788	0.989133
23	0.93241	0.99087	0.96587	0.94506	0.005586	13.04537	0.988105
24	0.94922	0.9239	0.91625	0.93307	0.006704	13.3087	0.985959
25	0.94635	0.98579	0.91869	0.94567	0.005377	16.47159	0.989043

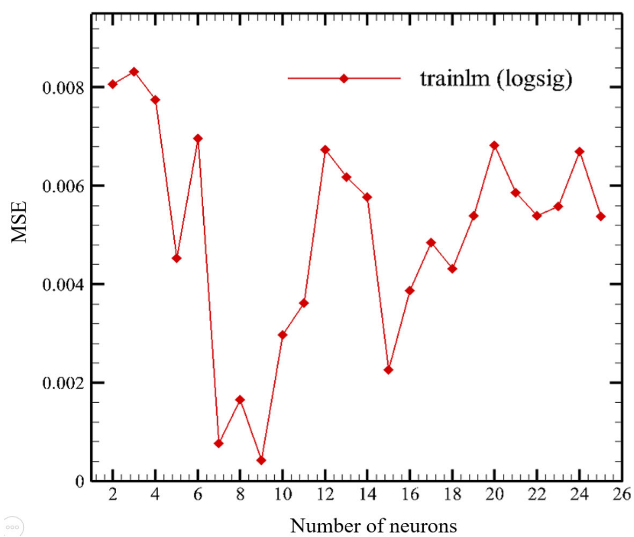

FIGURE 6. MSE variation with different numbers of neurons.

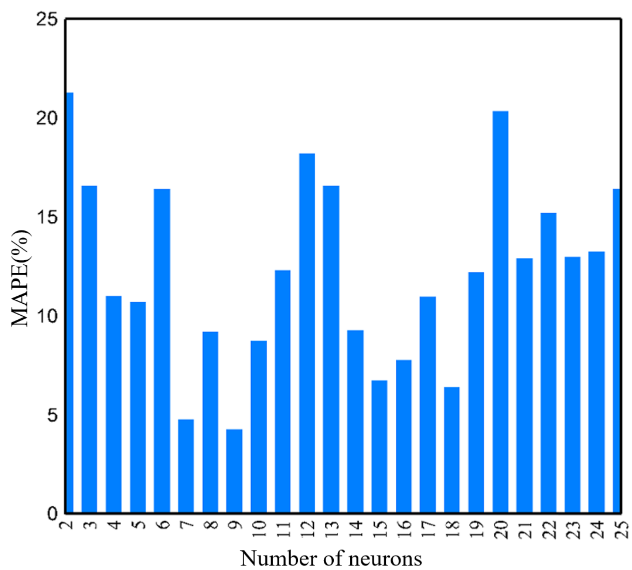

FIGURE 7. MAPE variation with different numbers of neurons.

total transportation cost. Some managerial insights obtained in this study are given as follows.

(a) All the constraints or criteria are tough to consider for the evaluation of objective function (total transportation cost in this case), decision-makers are not able to figure out which criteria to be chosen for the estimation of the objective function. This study provides a novel approach for selecting the best criteria derived from the linguistic terms taking the values in trapezoidal neutrosophic fuzzy numbers, which helps counter the vagueness or uncertainty in a much effective way.

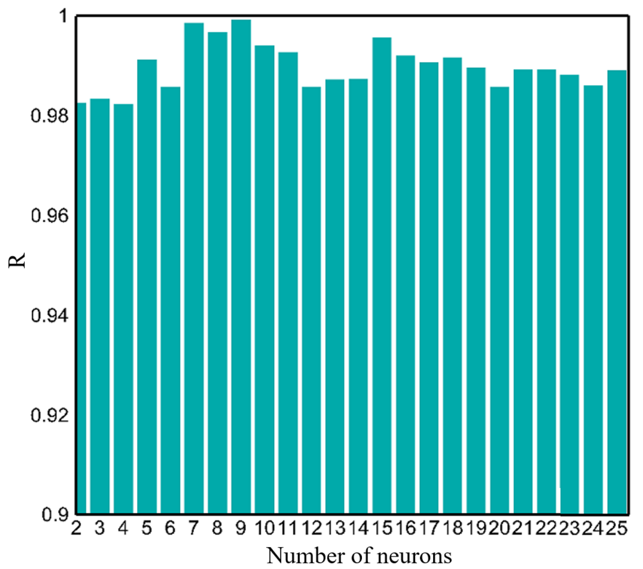

FIGURE 8. Pearson product-moment correlation coefficient R for different numbers of neurons.

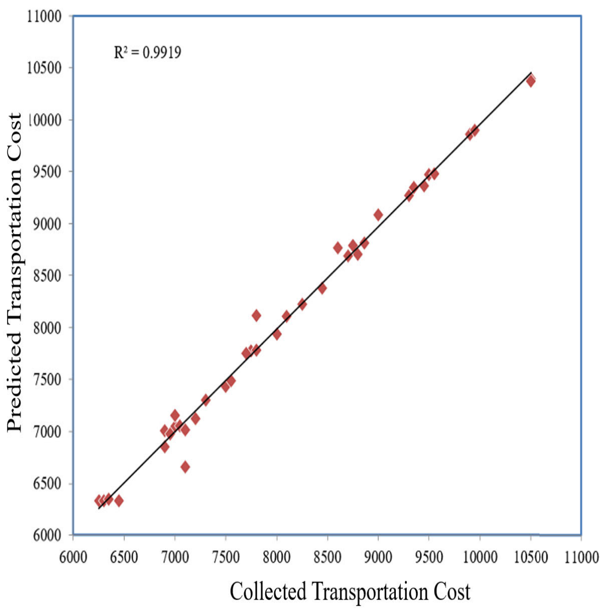

FIGURE 9. Correlation of predicted transportation cost with collected transportation cost.

- **(b)** A novel approach to choose the best criteria among multiple criteria is proposed through TNF-AHP.
- **(c)** The selection of a reasonable number of criteria reduces complexity and hence helps decision-makers obtain efficient solutions more straightforwardly.
- **(d)** Most researchers determine the total transportation cost through rigorous mathematical modeling, but this study provides a new approach to estimate the total transportation cost through the prediction using the historical data, so that the decision-makers are free of uncertainty theories in rigorous mathematical modeling.

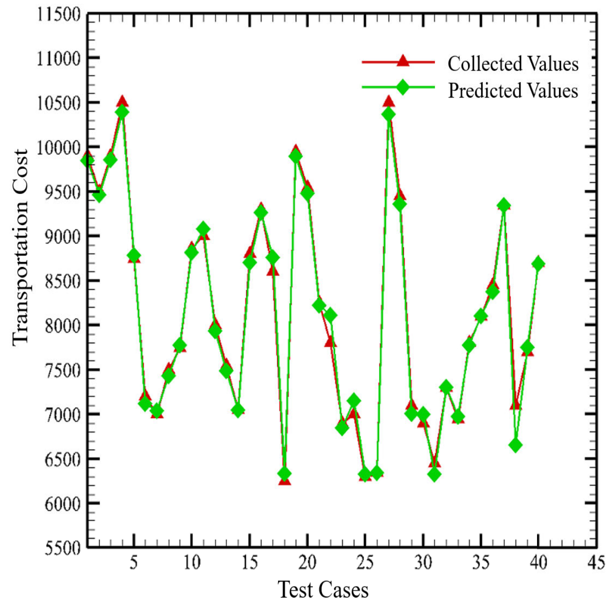

FIGURE 10. Comparison of predicted transportation cost with collected transportation cost for test cases.

TABLE 11. Comparison of ANN predicted transportation cost with collected transportation cost.

Collected transportation cost	Predicted transportation cost
10400	10210.04
6950	7115.52
6450	6456.32
7500	7603.32
9650	9652.86
9300	9410.81
6450	6599.30
7100	7173.89
10250	10445.75
8100	8167.38

- **(e)** This study emphasizes the needs of data warehousing for the operation-related data. The proposed TNF-AHP and ANN model can help the decision-maker conduct strategic planning and to respond quickly and effectively to the changes of the demands.
- **(f)** The road surface condition is challenging to consider in the mathematical model, and therefore, it is challenging to acknowledge the total transportation cost. Hence, ANN techniques to predict the total transportation cost are effective because it requires only knowledge about prior transportation cost regarding demand supplied and distance between the source and destination.
- **(g)** In this study, the prediction of total transportation costs is based on preliminary information, including all types of costs such as transportation costs, driver costs, loading-unloading costs, toll taxes, etc. Therefore the study provides an efficient and effective way for decision-makers to determine the total transportation costs through the prediction. Whereas considering all the costs and other constraints in the conventional

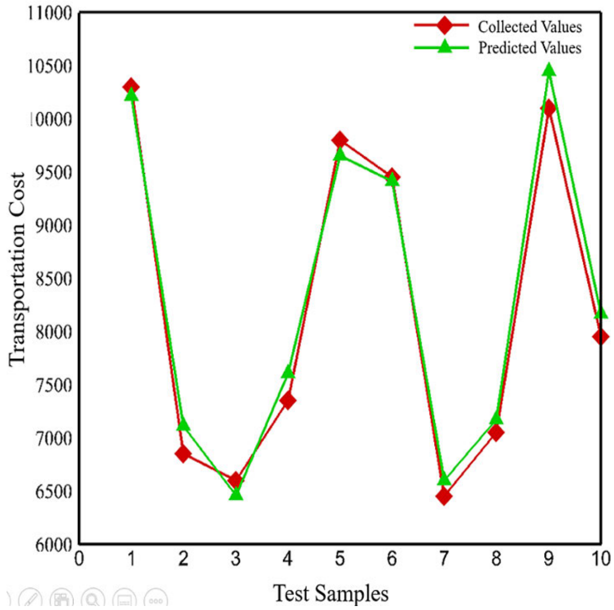

FIGURE 11. Comparison of predicted transportation cost with collected transportation cost for test samples.

transportation model is rigorous, uncertainty in the total transportation cost originates. Therefore, this study also eases to overcome uncertainties that arise in the conventional mathematical transportation model.

(h) Due to the dynamic system of fuel pricing in India, the unit transportation cost for the vehicle is not easy to regulate. Hence most of the time, the mathematical model for the transportation problems fails to address the preciseness in determining total transportation cost. Therefore, this study enhances the scope of utilization of ANN techniques to reach the preciseness towards the detection of total transportation cost.

This study contributes to the decision-makers for estimating the total transportation cost according to the demand and distance in TP.

B. LIMITATION OF THE PROPOSED WORK

The proposed TNF-AHP approach may obtain the averaged insights from a group of experts on selecting the best criteria without loss of generality, as shown in Step 2 of Section IV. However, the case study in this study includes only an opinion of a production manager in a company that provides the historical data on their transportation problem. Even within a company, different perspectives concerning alternative objectives may exist in a company. Therefore, obtaining the various experts' opinions would help in obtaining the best criteria for the company.

If the dataset has outliers, it was known that the performance measures (i.e., MSE and MAPE) might increase and R values decrease, leading to the inaccuracy of prediction. If there are outliers in the dataset, the ANN technique may fail to address the model's efficiency. For this study, a 6-9-1 topology has been adopted as an optimal topology of the ANN network. A trial-and-error method has been used to determine the appropriate topology as there is no specific method available for the determination. Hence, ANN took extra time to converge towards the accurate prediction of the total transportation cost.

IX. CONCLUSION

AHP exercise and efficiency could be advanced using neutrosophic fuzzy sets. In this paper, a TNF-AHP approach has been proposed for MCDM by implementing trapezoidal neutrosophic fuzzy numbers to prevent the imprecise, vague, and inaccurate point of view. The novel and effective TNF-AHP has been used first to obtain the best criteria from the set of criteria for further investigation to determine the total transportation cost through the ANN technique. After successfully obtaining the criteria, this study also investigates the utilization of the ANN model to emulate the prediction of the total transportation cost of a TP. Based on the collected data, an AI model such as ANN has been developed, and a comparison of results with collected data has been made. It has been found that the ANN model has the potential to map the input-output paradigms of TP with greater efficiency. A (6-9-1) topology with trainlm learning algorithm and logsig activation function for the ANN model is optimal for predicting TP's input-output pattern. The Pearson product-moment correlation coefficient R is 0.999156, indicating a high degree (99.92%) of the correlation between ANN predicted and collected data for the optimal network. Also, MSE and MAPE values are 0.000421 and 4.34484%, respectively, implying greater prediction efficiency of the optimal model. Finally, a comparison between ANN-based simulated transportation cost and collected transportation cost has been made, and it was found that the simulated output was very close to the collected output, which shows the higher efficiency of the ANN model in transportation problem

ANN is better to implement in any data-based decision-making problem in the real-life world. This study focuses on predicting transportation costs for a TP, but one can predict the demand for items and transportation costs of the TP with different input paradigms. AI models can be used where the total transportation cost does not just depend upon unit transportation cost. Furthermore, the TNF-AHP can be used for more complicated problems, such as multi-item multi-source problems where the supplier cannot fulfill all the end-users requirements. The proposed TNFAHP is used in supply chain management and inventory control management.

CONFLICT OF INTEREST

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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