Quadripartitioned Neutrosophic Pythagorean Soft Set for Financial Cost Estimation in E-Commerce Supply Chain Management

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Abstract

The idea of neutrosophic set (NS) from a philosophical viewpoint is a generality of the theory of indeterminacy FS (IFS) and fuzzy set (FS). A NS is considered by a falsity, a truth and indeterminacy membership functions and all membership amount is an actual standard or a non-standard sub-set of the non-standard unit interval]−0, 1+[. E-commerce is successful for the growth of novel business methods and should be constantly improved in the numerous decades. According to the growing E-commerce, supply chain management (SCM) has been strongly affected as we are now previously overcome by achievement in either developed or developing economies. Nowadays, E-commerce in advanced economy characterizes the newest lead of possibility in physical distribution systems and SCM, even if it emerging economy, e-commerce market is even in its infancy however, it is increasing and become integral part of commercial life. This paper presents a Quadripartitioned Neutrosophic Pythagorean Soft Set-Based Prediction Model for Supply Chain Management **(**QNPSSPM-SCM) model Using Hybrid Optimization Algorithms. The proposed QNPSSPM-SCM technique is for presenting an advanced E-commerce in SCM using advanced optimization techniques. At first, the min-max normalization method has been applied in the data pre-processing stage to convert input data into a beneficial pattern. In addition, the presented QNPSSPM-SCM system executes quadripartitioned neutrosophic Pythagorean soft set (QNPSS) technique for the prediction process. At last, the hybrid grey wolf optimization and teaching-learning-based optimization (GWO-TLBO) algorithm fine-tunes the hyperparameter values of the QNPSS model optimally and results in better performance of prediction. The experimental validation of the QNPSSPM-SCM method is verified on a benchmark database and the outcomes are determined regarding different measures. The experimental outcome underlined the development of the QNPSSPM-SCM method in prediction process.

Keywords: Neutrosophic Set; Quadripartitioned Neutrosophic Pythagorean Soft Set; Fuzzy Set (FS); E-commerce; Financial Cost; Supply Chain Management; Hybrid Optimization Algorithms

1. Introduction

Neutrosophic set (NS) is considered the more effective tool for modelling indeterminate in the problem of decision-making and its expansions like interval NS (INS), interval complex NS (ICNS), and complex NS (CNS) [1]. The effective tools to demonstrate vagueness and uncertainty in decision-making have been the most generalization of the fuzzy set, intuitionistic fuzzy set (IFS), and classical set through integrating three degrees of falsehood, indeterminacy, and truth of a validated declaration. It was used in several processes of decision-making. INS and CNS were presented for adopting NS with a further complex case [2]. Electronic commerce (i.e., e-commerce) is one of the common modes of business where companies may sell products and services over social

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media platforms and customers may visit their online stores anywhere in the world. E-commerce companies create their digital network and evaluate their marketing process by offering more competitive products and services to attract many customers [3]. With the advancement of the Internet, e-commerce transactions have increased and witnessed emerging markets. This was particularly true during the pandemic with continuous advancement in e-commerce marketing [4]. It is more vital in academia and business. In the meantime, it is obvious that the various issues of management are to be examined; e-commerce is developing as the broadly explored domain in the practice of business [5].

Depending upon the thriving E-commerce, supply chain management (SCM) was influenced significantly and we were already overwhelmed with their success in both emerging and emerging economies. The objective of SCM is to enable member organizations to collaborate closely in long-term relationships to increase the supply chain benefit as a whole [6]. In the E-commerce SCM, the two forms of business modules are business-to-business (B2B) and business-to-consumer (B2C). In the B2C method, a business web site is a place where all transactions take place between business and customer [7]. In this method, a customer visits the web site and places to buy a catalog. Once the order is received, the company will send the goods to the consumer. The main characteristics of these techniques are promoting highly to get more customers, higher investing of software and hardware, and decent service to customers [8]. B2B denotes a condition where one company creates commercial transactions with another therefore, the transaction capacity of B2B is higher than the capacity of B2C. In a classic supply chain, there are more B2B transactions containing raw materials and sub-components, the unique B2C transaction particularly, the sales of completed products to the user [9]. The buying of B2B products is more dangerous than the buying of B2C products. This is due to the buying of the mistaken products or volume that may keep the whole purchase at risk [10].

The purpose of this study is to develop a Quadripartitioned Neutrosophic Pythagorean Soft Set-Based Prediction Model for Supply Chain Management (QNPSSPM-SCM) method utilizing Hybrid Optimization Algorithms. For achieving it, the proposed QNPSSPM-SCM employs min-max normalization approach in the data pre-processing step. Furthermore, the neutrosophic Pythagorean soft set (QNPSS) model is deployed for the prediction process. Eventually, the hybrid grey wolf optimizer and teaching-learning based optimizer (GWO-TLBO) is designed for hyperparameter tuning model. The experimental validation of the QNPSSPM-SCM method is verified on a benchmark database and the outcomes are determined under different measures.

The rest of the paper is designed into four sections. The Section 2 presents literature work. Then, the proposed methodology used in this paper is explained in Section 3. Result analysis are given in Section 4. At last, Section 5 provides conclusion.

2. Literature Work

Li and Gong [11] proposed a combined key for SCM that depends upon mobile-interaction technologies through the S2B2C e-commerce platforms. The goal of upgrading sustainability, transparency, and intelligence of the supply-chain through new technology. This study concentrates on the execution technology for mobile devices in SCM besides the implementation and design of a demand prediction technique and procedure reliant on application of mobile. Goswami et al. [12] investigate further the possibility of AI-based SCM as an innovative tool proficient in changing supply-chain processes and guiding in a fresh perspective. In a dynamic business environment, where efficiency and agility are supreme, AI acts as to redefine the supply-chain in what way it is operating. This research starts with a thorough investigation of the important concept of AI and applications of the manifold into SCM, explaining their flexibility through several factors of the supply-chain, from inventory optimization to demand forecasting. Ye [13] presented a model that grows a Cold-Supply Chain Optimization method and a Short-Term Demand-based Deep Neural Network by predicting the capacity of a product that has been purchased. The DNN technique proposes a cold-supply-chain demand prediction structure centred on multi-layer BNN for forecasting the short-term demand for e-commerce merchandise.

Sindakis et al. [14] explored the roles of inter-relationships between e-commerce supply-chain participants in determining feasibility results. It incorporates a qualitative method, illustrating Resource Dependency Theory (RDT) and Sustainable SCM (SSCM) for gaining in-depth realization of feasibility in e-commerce supply-chains. In [15], current cyber security vulnerabilities and measures in the e-commerce supply-chains when suggesting efficient tactics to alleviate risk possibilities. By the wider related works, this study highlights several cybersecurity difficulties that came across e-commerce businesses, comprising ransomware attacks, supply chain disruptions, and data breaches triggered by cyber-attacks on carrier services.

Wang [16] used the integration of ML methods and multi objective optimizer for enhancing the performance of supply-chain in CBEC. Then, the structure for the intellectual CBEC-enabled IoT technique was presented. With the use of ML methods in these procedures, effort is created to increase the function of supply-chain by predicting demand capacity. The prediction method employed in this introduced model is an ensemble structure depend upon

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Adaptive Neuro-Fuzzy Inference System (ANFIS) that uses a weighted average method for predicting demand capacity for every shop. Mathur et al. [17] explore the combination of logistics in operations of the supply-chain, emphasizing their effect on disruption management and supply-chain resilience. This study begins by investigating the important method of SCM and the understanding of SCM and e-commerce. Then it investigates the concepts of identifying key elements and their inter-relationships and supply-chain adaptability. The effect of logistics on disruption management and supply-chain resilience was examined, illustrating visions from the present works.

3. Materials and Methods

In this manuscript, we have proposed a QNPSSPM-SCM model. The QNPSSPM-SCM technique is proposed in this paper for presenting an advanced E-commerce in SCM using advanced optimization techniques. It consists of dissimilar stages like min-max normalization, the predication process using QNPSS, and GWO-TLBO-parameter Tuning Method. Figure 1 represents the complete workflow of QNPSSPM-SCM model.

Stage 1: Pre-processing

Primarily, the min-max normalization model has been applied in the data pre-processing phase for transforming input data into a beneficial format [18]. Min-max normalization is a data pre-processing technique applied in SCM for scaling mathematical data inside a predefined interval, normally [0, 1]. It aids in normalizing dissimilar metrics, like inventory levels, demand predictions, and transportation charges, guaranteeing good comparison and increasing the precision of predictive methods. By converting data correspondingly, this method stops larger values from controlling smaller ones, improving optimizer methods and decision-making procedures. This model is mostly beneficial in ML applications for demand predicting, logistics optimization, and supplier evaluation. It furthermore increases convergence speed in optimizer difficulties, resulting in a more effective allocation of resources.

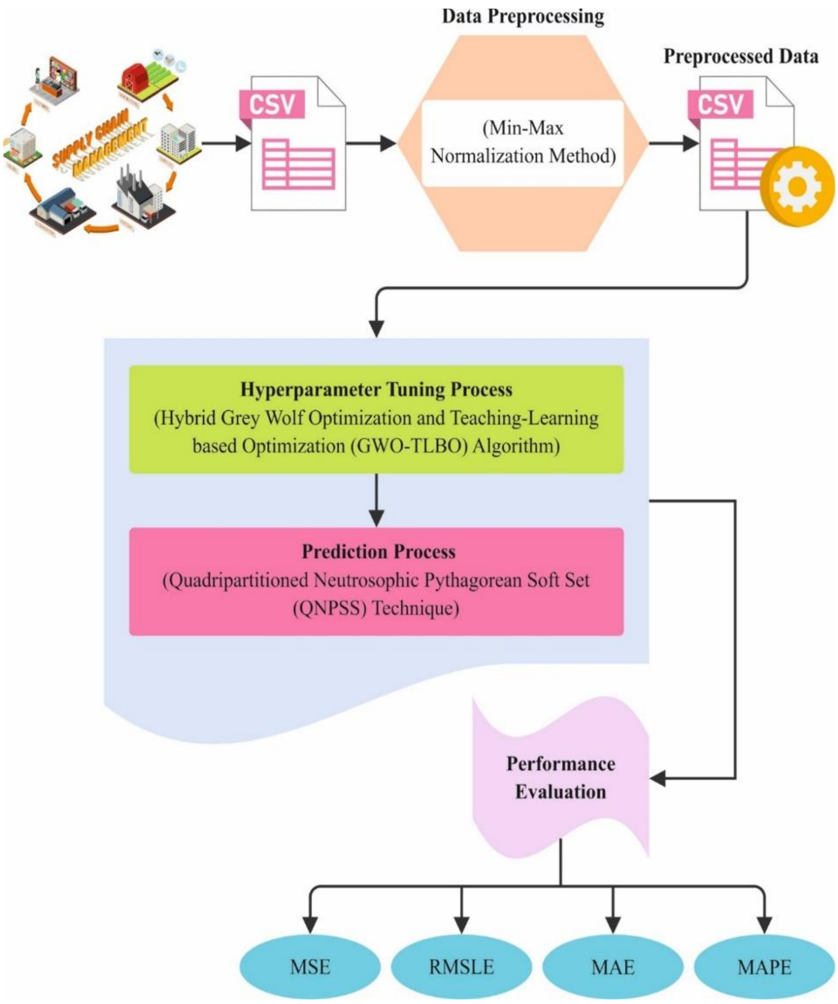

Figure 1. Complete workflow of QNPSSPM-SCM model

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Stage 2: Predication Process using QNPSS

Furthermore, the proposed QNPSSPM-SCM system implements QNPSS model for the process of prediction [19].

Definition: 3.1

Consider X is a first set of universe and E is parameter set. Considering a set of non-empty A on E, assume $P(X)$ signify the collection of each Quadripartitioned neutrosophic pythagorean set of X. The set (F, A) is named QNPSS above X, whereas F refers to mapping provided by $F: A \to P(X)$.

Definition: 3.2

In QNPSS, A is limited in other QNPSS B for example: $A \subseteq B$ when $T_A(x) \leq T_B(x), C_A(x) \leq C_B(x), U_A(x) \geq U_B(x)$ and $F_A(x) \geq F_B(x)$

Definition: 3.3

The addition of the QNPSS (F, A) on X signified by $(F, A)^c$ and is delineated as

$$F^c(x) = \{< x, F_A(x), U_A(x), C_A(x), T_A(x) >: x \in X\}$$

Definition:3.4

Assume X is a non-empty sets, $A =< x, T_A(x), C_A(x), U_A(x), F_A(x) > and$

$B =< x, T_B(x), C_B(x), U_B(x), F_B(x) > are$ QNPSS. Formerly

$$A \cup B =< x, \max(T_A(x), T_B(x)), \max(C_A(x), C_B(x)), \min(U_A(x), U_B(x)), \min(F_A(x), F_B(x)) >$$

$$A \cap B =< \mathrm{x}, \min(T_A(x), T_B(x)), \min\,(C_A(x), C_B(x)), \max\,(U_A(x), U_B(x)), \max\,(F_A(x), F_B(x) >$$

Definition: 3.5

A QNPSS (F, A) across the universe X is empty neutrosophic-pythagorean soft-sets regarding the parameter A when

$T_{F(e)} = 0, C_{F(e)} = 0, U_{F(e)} = 1, F_{F(e)} = 1, \forall x \in \mathrm{X}, \forall e \in A$. It can be signified by 0_X

Definition: 3.6

A QNPSS (F, A) upon the universe X is considered as universe neutrosophic soft set concerning the parameter A when

$T_{F(e)} = 1, C_{F(e)} = 1, U_{F(e)} = 0, F_{F(e)} = 0, \forall x \in \mathrm{X}, \forall e \in A$. It was signified by 1_X

Remarks: $0_X^c = 1_X$ and $1\ c_X = 0_X$

Definition: 3.7

Assume that A and B be dual QNPSS on X then $A \setminus B$ is

$$A \setminus B =< \mathrm{x}, \min(T_A(x), F_B(x)), \min(C_A(x), U_B(x)), \max(U_A(x), C_B(x)), \max\,(F_A(x), T_B(x)) >$$

Definition: 3.8

F_E is specified as complete QNPSS through X if $F(e) = 1_X$ for some $e \in E$. Identified by X_E

Definition: 3.9

F_E stated that comparative null QNPSS above X when $\mathrm{F}(e) = 0_X$ for some

$e \in E$. Indicated using $\emptyset_E$

Clearly $\emptyset_E = X_E^C$ and $X_E = \emptyset_E^c$

Definition: 3.10

The inverse of a QNPSS (F, A) above X can be further described as $(F_t A)^c = U_E \setminus F(e)$ for every $e \in A$.

Note that: symbolize X_E by X in proposition proof.

Definition: 3.11

If (F, A) and (G, B) are dual QNPSS then (F, A) AND (G, B) is specified by

$(F, A) \wedge (G, B)$ and is delineated by $(F, A) \wedge (G, B) = (H, A \times B)$

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While $H(a,b)=F(a)\cap G(b)\forall a\in A$ and $\forall b\in B_t$ whereas $\cap$ refers to operation connection of QNPSS.

Definition: 3.12

When (F,A) andj (G,B) be dual QNPSS after(F,A) OR (G,B) represented by $(F,A)V(G,B)$ and is outlined by $(F,A)V(G,B)=(K,A\times B)$ while $K(a,b)=F(a)\cup G(b)\forall a\in A$ and $\forall b\in B$, whereas $\cup$ denote process combination of QNPSS.

Theorem: 3.13

Assume that (F,A) and (G,A) is a QNPSS across the universe X. Next, the succeeding is true.

1. $(F,A)\subseteq(G,A)$ iff $(F,A)\cap(G,A)=(F,A)$
2. $(F,A)\subseteq(G,A)$ iff $(F,A)\cup(G,A)=(F,A)$

Proofs:

(1) Let $(F,A)\subseteq(G,A)$, formerly $F(e)\subseteq G(e)$ for every $e\in A$ and $(F,A)\cap(G,A)=(H,A)$.

As $H(e)=F(e)\cap G(e)=F(e)$ for each $e\in A$, by description $(H,A)=(F,A)$.

Assume that $(F,A)\cap(G,A)=(F,A)$ and $(F,A)\cap(G,A)=(H,A)$.

As $H(e)=F(e)\cap G(e)=F(e)$ for every $e\in A$, understand that $F(e)\subseteq G(e)$ for each $e\in A$.

Therefore $(F,A)\subseteq(G,A)$.

(2)The proof is related to (1).

Theorem: 3.14

Assume that (F,A), (G,A), (H,A), and (S,A) are QNPSS across the universe X. After the succeeding are true.

1) $(F,A)\subseteq(G,A)$ iff $(G,A)^c\subseteq(F,A)^c$
2) If $(F,A)\cap(G,A)=\emptyset_A$, then $(F,A)\subseteq(G,A)^c$
3) If $(F,A)\subseteq(G,A)$ and $(H,A)\subseteq(S,A)$ then $(F,A)\cap(H,A)\subseteq(G,A)\cap(S,A)$
4) If $(F,A)\subseteq(G,A)$ and $(G,A)\subseteq(H,A)$ then $(F,A)\subseteq(H,A)$

Proofs:

(i) Let $(F,A)\cap(G,A)=\emptyset_A$.Formerly $\mathrm{F}(e)\cap G(e)=\emptyset$.

Thus, $F(e)\subseteq U\setminus G(e)=G^c(e)$ for every $e\in A$.

As a result, have $(F,A)\subseteq(G,A)^c$

Proofs of (ii) and (iii) are understandable.

(iv) $(F,A)\subseteq(G,A)\Leftrightarrow F(e)\subseteq G(e)$ for each $e\in A$.

$\Leftrightarrow (G(e))^c\subseteq(F(e))^c$ for every $e\in A$. $\Leftrightarrow G^c(e)\subseteq F^c(e)$ for each $e\in A$.

$$\Leftrightarrow (G,A)^c\subseteq(F,A)^c$$

Definition: 3.15

Assume that I is a random index $\{(F_i,A)\}_{i\in I}$ is a sub-family of QNPSS through the universe X.

(i)The intersection of these QNPSS is the QNPSS (H,A) whereas $H(e)=\cup_{i\in I}F_i(e)$ for all $e\in A$.

They mark $\cup_{i\in I}(F_i,A)=(H,A)$

(ii) The union of these QNPSS is the QNPSS (M,A) while $M(e)=\cap_{i\in I}F_i(e)$ for all $e\in A$.

Writting $\cap_{i\in I}F_i(e)=(M,A)$

Theorem: 3.16

Suppose that I is a random index collection and $\{(F_i,A)\}_{i\in I}$ is a sub-family of QNPSS across the universe X. Formerly

1. $\left(\cup_{i\in I}(F_i,A)\right)^c=(\cap_{i\in I}(F_i,A))^c$
2. $(\cap_{i\in I}(F_i,A))^c=\left(\cup_{i\in I}(F_i,A)\right)^c$

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Proofs:

(i) $\left(\cup_{i\in I}(F_i, A)\right)^c = (H, A)^C$, By description $H^c(e) = X_E \setminus H(e) = X_E \setminus\cup_{i\in I} F_i(e) = \cap_{i\in I}\left(X_E \setminus F_i(e)\right)$ for every $e \in A$. Conversely, $(\cap_{i\in I}(F_i, A))^c(K, A)$.

By description, $K(e) = \cap_{i\in I} F_i(e) = \cap_{i\in I}\left(X - F_i(e)\right)$ for each $e \in A$.

(ii) It is clear.

Note that: represent $\emptyset_E$ by $\emptyset$ and X_E by X.

Stage 3: GWO-TLBO -Parameter Tuning Method

The hybrid GWO-TLBO model adjusts the hyperparameter values of the QNPSS method optimally and outcomes in improved prediction performance. The proposed GWO-TLBO model was modified for both GWO and TLBO [20]. The GWO is an optimizer technique, which is stimulated by the grey wolves hunting behavior. Grey wolves form a hierarchy in their behavior of hunting. This hierarchy contains leaders and lower groups. The hierarchical structure is stimulated as follows. They are classified as α wolf, β wolf, δ wolf and ω wolf correspondingly. At the top of the hierarchical structure, the α wolf is the leader of the group, who manages group dynamics and makes important decisions. This is followed by β wolf and others. Next, there are δ wolves that follow the wolves in the upper sets of the hierarchy and do tasks like surveillance and exploration. In the lowest type, ω wolves. They create the rest of the population and collaborate with other wolves. The foremost modules of the GWO model are the hierarchy of wolves and behavior of hunting. Hunting behavior includes encircling, searching, and hunting. This behavior is stated as a hunting method in a mathematical form. At first, wolves are demonstrated in Eqs. (1) and (2) to hunt and enclose their prey.

$$D = |C.X_T(t) - X(t)| \qquad (1)$$

$$X(t+1) = X_T(t) - A.D \qquad (2)$$

Where D refers to the distance between wolf and prey. $X_T(t)$ represents the target prey location at $t - th$ time . $X(t)$ refers to a grey wolf location at $t - th$ time. A and C refer to coefficients that affect the distance among the prey and wolf and the location of the target prey, correspondingly. A and C are defined in Eqs. (3) and (4), correspondingly. A is a parameter that appears as the convergence factor and reduces towards 0 with every iteration in 2.

$$A = 2.a.r_1 - a \qquad (3)$$

$$C = 2.r_2 \qquad (4)$$

r_1 and r_2 refers to generated numbers at random from 0 to 1. A and C mean a search behavior, which defines the exploitation and exploration behavior of the technique. If the coefficient A is higher than 1 at every iteration, the wolves do their hunt behavior with a global search behavior. Or else, if A is lesser than 1, then the wolves attempt the target and a behavior of an exploitation is employed.

The behavior of wolves hunting prey is stated in Eqs. (5-7). For the wolves to travel near the target, , β , and δ wolves in the hierarchy play a vital part in defining the location of target robot with prey. Here, α, β and δ wolves denote the best candidate solutions correspondingly. The location details of the α, β and δ wolves are set in Eqs. (5) and (6).

$$D_\alpha = |C_1.X_\alpha - X|$$

$$D_\beta = \left|C_2.X_\beta - X\right| \qquad (5)$$

$$D_\delta = |C_3.X_\delta - X|$$

$$X_1 = X_\alpha - A_1.D_\alpha$$

$$X_2 = X_\beta - A_2.D_\beta \qquad (6)$$

$$X_3 = X_\delta - A_3.D_\delta$$

While, C_1, C_2, C_3 and A_1, A_2, A_3 are randomly generated coefficients resultant as per Eqs. (3) and (4). The wolf in the exploration sequence defines the novel location by averaging the sites of these 3 wolves. Eq. (7) defines the novel position established.

$$X(t+1) = \frac{X_1+X_2+X_3}{3} \qquad (7)$$

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The GWO technique stages are employed for determining an exploration and exploitation behavior in the searching procedure. While wolves hunt for a global solution, they concentrate on the local solution when they contact the objective.

The TLBO technique is a population-based optimizer model inspired by student and teacher behavior. In the population, they hunt for a solution to get a global solution. TLBO contains dual phases such as "Teaching Phase" and "Learning Phase". During the level of teaching, the teacher utilizes experience to upsurge the average outcome of the class. The class is definite as $\{X_1, X_2, \ldots, X_N\}$. N denotes a no. of classes. The teacher signifies the finest solution. It is meant by $X_{Teacher}$. The average of the class is meant by M. Eq. (8) is stated by M.

$$M_\tau = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{8}$$

The upgrading of students' locations is defined by Eq. (9).

$$X_{new} = x_{old} + r_T.(X_{Teacher} - TF.M) \tag{9}$$

While TF denotes the training factor. TF means a factor that defines how much information the teacher delivers. r_T refers to a training factor. r_T denotes a generated amount at random within the range of $[01]$. TF is computed as stated in Eq. (10).

$$TF = round[1 + rand(0,1)] \tag{10}$$

During the learning stage, students progress their knowledge over information gathered from the teacher or by interrelating with other students. The method of individual and communicating learning differs. The fitness function values of X_i and X_j of dual chosen students at random are equated as stated in Eqs. (11) and (12).

$$X_{new} = X_{old} + r_L.\left(X_i - X_j\right)\ f(X_i) < f\left(X_j\right) \tag{11}$$

$$X_{new} = X_{old} + r_L.\left(X_j - X_i\right)\ otherwise \tag{12}$$

While r_L denotes a randomly generated amount among [0 and 1]. X_{old} contains the previous result here.

The proposed model uses the beneficial features of GWO and TLBO techniques. With GWO, novel locations are defined hierarchically, and with TLBO, the learning and teaching stages allow individuals to study over experience handover and communication. The TLBO technique yields an optimum value of fitness function than the finest solution α wolf in the GWO model. It has the benefit of being robust in the local solution and the target solution. The TLBO technique displays higher performance in global optimal solutions. TLBO achieves a balanced exploration and distribution and travels a huge solution space, while GWO concentrates on the target by decreasing the searching space as it attempts the target. The GWO-TLBO model ranks the finest fitness value of the population wolves as in GWO to discover the locations of α, β, and δ wolves. In Eq. (7), the novel location of GWO is defined by averaging the locations of these 3 wolves. For learning phase, it utilizes the location of α, β, and δ for the computed student mean M. Then the TLBO learning stage is employed. In Eq. (8), a class average signifies the solution of M. At last, the α position of the GWO model has been utilized as the finest solution. If the iteration cycle is done, then the location α has been affected by both GWO and TLBO algorithms after the procedure. The location is upgraded to reach out to the finest solution, which is defined in Eq. (9).

In this paper, the GWO-TLBO is applied to determine the hyperparameter included in the QNPSS method. The MSE is measured as the objective function and is described as shown.

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \tag{13}$$

While M and L characterize the resulting value of data and layer consistently, y_j^i and d_j^i implies the achieved and proper sizes for j^{th} unit from the resulting layer of network in time t consistently.

4. Result Analysis

In this section, the experimental validation of QNPSSPM-SCM technique is inspected under Supply chain dataset [21].

Table 1 and Figure 2 shows the training set (TRAST) and testing set (TESST) solution of QNPSSPM-SCM technique under different metrics. In TRAST, the QNPSSPM-SCM methodology obtains MSE, RMSLE, MAE, and MAPE of 0.0433, 0.1435, 0.1768, and 0.3113, respectively. Besides, on TESST, the QNPSSPM-SCM system gains MSE, RMSLE, MAE, and MAPE of 0.0432, 0.1418, 0.1738, and 0.3002, respectively.

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Table 1: TRAST and TESST outcome of QNPSSPM-SCM model under various metrics

Metrics	Training Set	Testing Set
MSE	0.0433	0.0432
RMSLE	0.1435	0.1418
MAE	0.1768	0.1738
MAPE	0.3113	0.3002

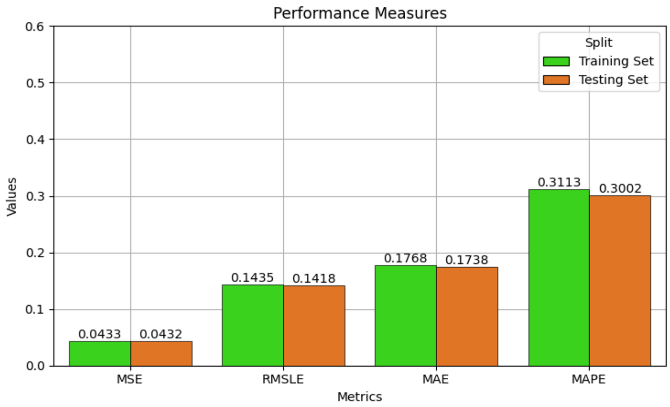

Figure 2. TRAST and TESST outcome of QNPSSPM-SCM model under various metrics

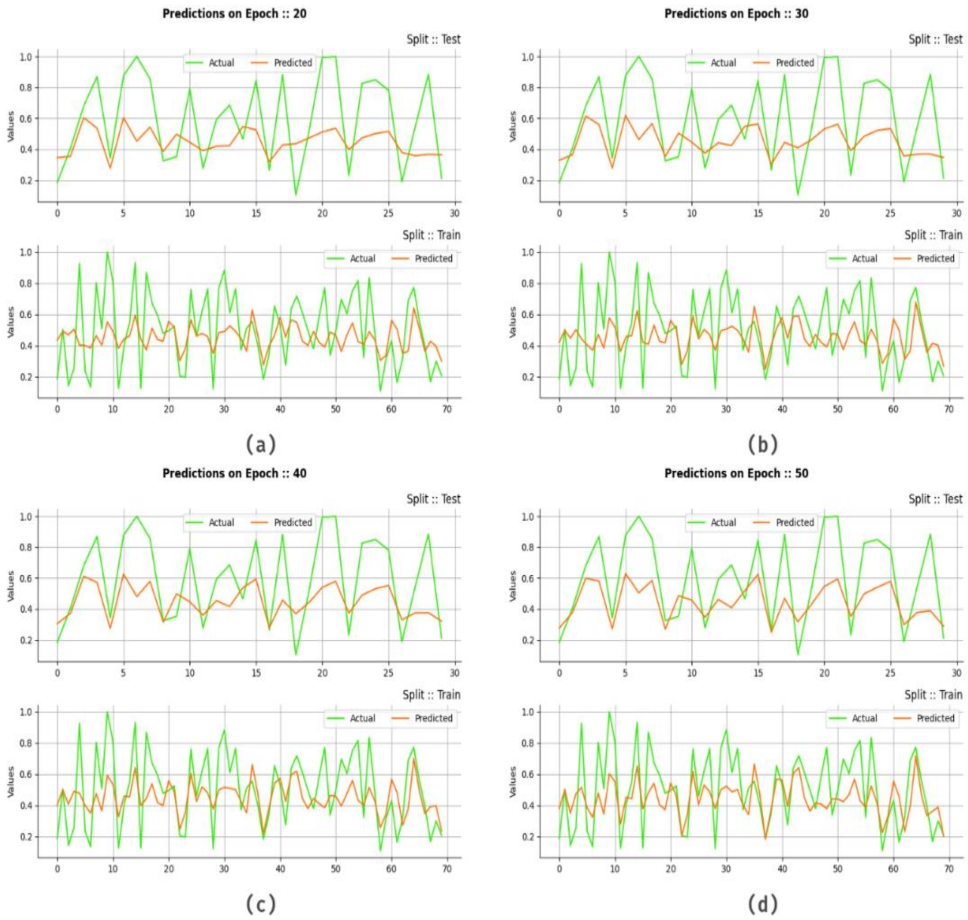

Figure 3. Actual vs Prediction outcome of QNPSSPM-SCM model on (a-d) Epochs 20-50

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Figure 3 illustrates the prediction performance of QNPSSPM-SCM technique under epochs 20-50. The figure specifies that the QNPSSPM-SCM method appropriately forecast the solution. It is also noted that the predicted values by the QNPSSPM-SCM approach is closer to an actual values.

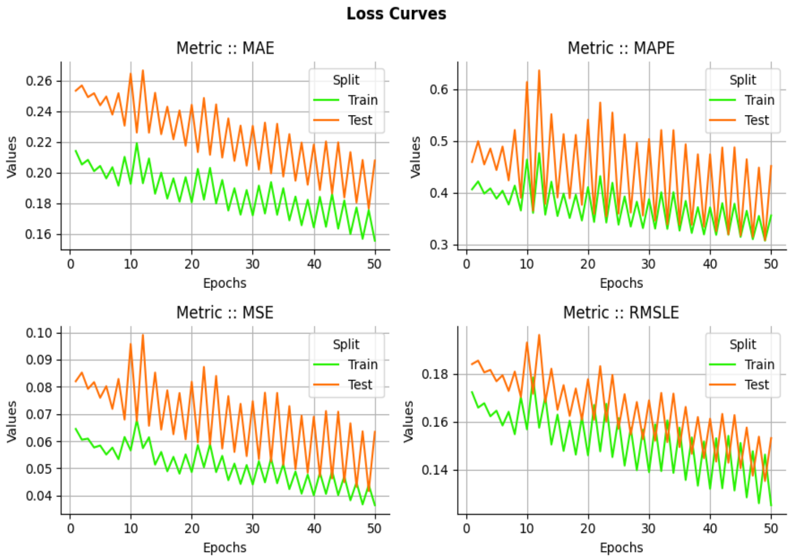

Figure 4. Loss curves of QNPSSPM-SCM model under various metrics

In Figure 4, the TRAN loss (TRANLOS) and VALN loss (VALNLOS) curve of the QNPSSPM-SCM methodology is illustrated. The loss values are calculated through an interval of 0-50 epochs. It is depicted that the either values exemplify to reduce tendencies, reporting the proficiency of the QNPSSPM-SCM system in balancing a trade-off between generalization and data fitting. The incessant decrease in loss values moreover ensures the maximum outcome of the QNPSSPM-SCM method and adjust the prediction performance over time.

Table 2 illustrates the comparison solution of the QNPSSPM-SCM approach with present approach under several metrics [22, 23].

Table 2: Comparative analysis of AIB2BSE- NFRST model with existing models

Algorithm	**MSE**	**RMSLE**	**MAE**
Logistic Regression	0.0928	0.6768	0.6458
Gradient Boosting	0.0874	0.6038	0.5628
SVM	0.0784	0.5468	0.4918
XGBoost	0.0727	0.4578	0.4418
Deep CNN	0.0652	0.3858	0.3878
BiLSTM	0.0589	0.3128	0.3148
DR-SCM	0.0504	0.2228	0.2588
QNPSSPM-SCM	0.0432	0.1418	0.1738

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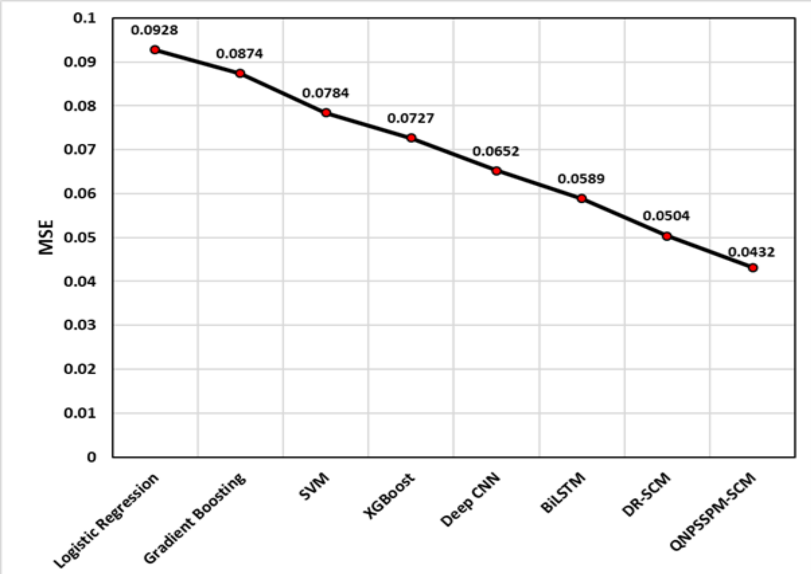

Figure 5. MSE outcome of QNPSSPM-SCM model with existing algorithms

Figure 5 represents the MSE performance of QNPSSPM-SCM model with current technique. Under MSE, the projected QNPSSPM-SCM system attains smaller MSE of 0.0432, while the present methodologies namely Logistic Regression, Gradient Boosting, SVM, XGBoost, Deep CNN, BiLSTM and DR-SCM are attained higher MSE of 0.0928, 0.0874, 0.0784, 0.0727, 0.0652, 0.0589, and 0.0504, correspondingly.

Figure 6 exposes the RMSLE solution of QNPSSPM-SCM method with present approaches. Under MAPE, the current system like Logistic Regression, Gradient Boosting, SVM, XGBoost, Deep CNN, BiLSTM and DR-SCM are gained maximum RMSLE of 0.6768, 0.6038, 0.5468, 0.4578, 0.3858, 0.3128, and 0.2228, correspondingly. Whereas, the presented QNPSSPM-SCM approach is attained smaller RMSLE solution of 0.1418.

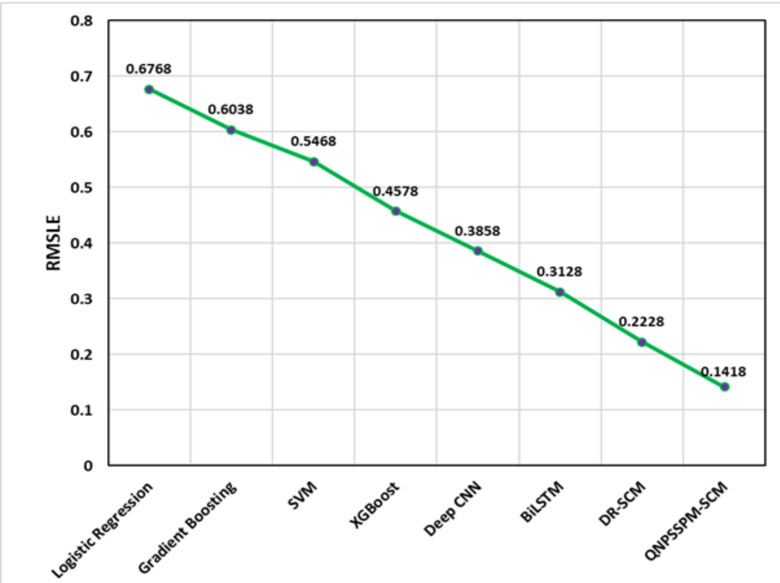

Figure 6. RMSLE outcome of QNPSSPM-SCM model with existing algorithms

The MAE solution of QNPSSPM-SCM approach with present techniques are illustrates in Figure 7. Under MAE, the projected QNPSSPM-SCM method attains minimal MAE of 0.1738, although the present approaches namely Logistic Regression, Gradient Boosting, SVM, XGBoost, Deep CNN, BiLSTM and DR-SCM are attained higher MSE of 0.6458, 0.5628, 0.4918, 0.4418, 0.3878, 0.3148, and 0.2588, respectively.

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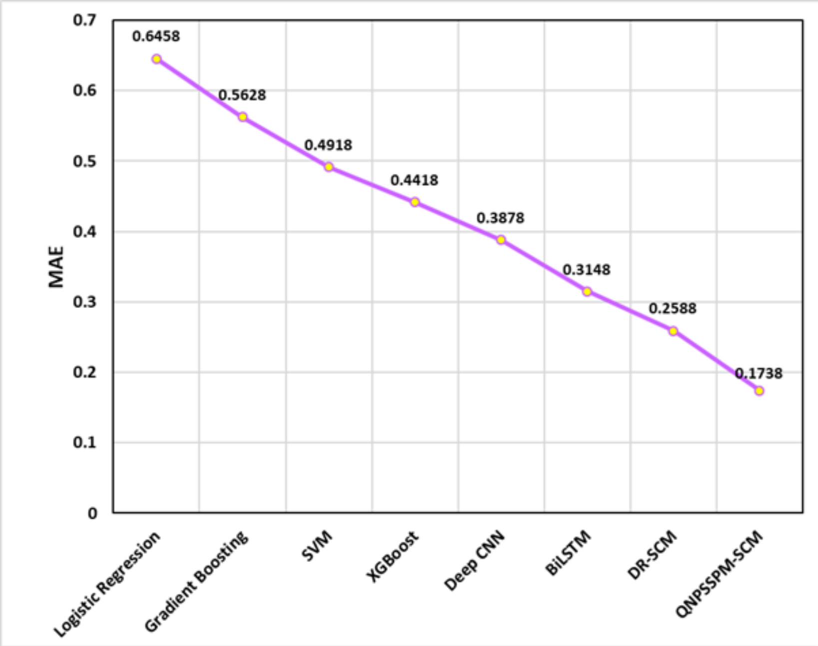

Figure 7. MAE outcome of QNPSSPM-SCM model with existing algorithms

Table 3 and Figure 8 demonstrates the time solution of QNPSSPM-SCM technique with present methodologies. Depending on time, the presented QNPSSPM-SCM system is attained minimal time of 7.96sec, although the present methods like Logistic Regression, Gradient Boosting, SVM, XGBoost, Deep CNN, BiLSTM and DR-SCM are gained higher time of 10.25sec, 17.69sec, 14.02sec, 18.81sec, 19.59sec, 11.74sec, and 18.04sec, respectively.

Table 3: Time outcome of QNPSSPM-SCM model with existing algorithms

Algorithm	**Time (sec)**
Logistic Regression	10.25
Gradient Boosting	17.69
SVM	14.02
XGBoost	18.81
Deep CNN	19.59
BiLSTM	11.74
DR-SCM	18.04
QNPSSPM-SCM	7.96

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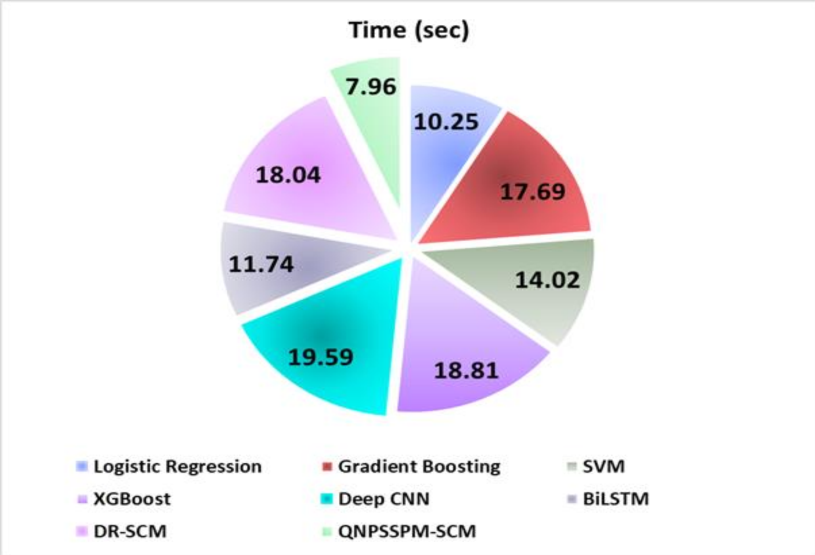

Figure 8. Time outcome of QNPSSPM-SCM model with existing algorithms

5. Conclusion

This paper presents a QNPSSPM-SCM model Using Hybrid Optimization Algorithms. The proposed QNPSSPM-SCM technique is for presenting an advanced E-commerce in SCM using advanced optimization techniques. At first, the min-max normalization method has been applied in the data pre-processing stage to convert input data into a beneficial pattern. In addition, the QNPSS technique is deployed for prediction process. At last, the hybrid GWO-TLBO methodology fine-tunes the hyperparameter values of the QNPSS model optimally and results in better performance of prediction. The experimental validation of the QNPSSPM-SCM method is verified on a benchmark database and the outcomes are determined regarding different measures. The experimental outcome underlined the development of the QNPSSPM-SCM method in prediction process.

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