



# Analyzing and Interpretation of Kernel Neutrosophic Set Based Machine Learning Model for Cost Estimation of Multi Product Supply Chain Management Systems

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## Abstract

Neutrosophic set (NS) is a novel devise to handle uncertainty considering the memberships of truth T, indeterminacy I, and falsity F satisfying. It is employed to illustrate the indefinite data more appropriately and precisely than an intuitionistic fuzzy set. The search for cost information over the supply chain is very significant for controlling costs that aid in enhancing and beginning activities in organizations in the value chain. In today's intricate supply networks, sharing data among suppliers and buyers is important for sustainable competitive benefit. Particularly, for both business partners, cost information is extremely appropriate in buying conditions. As per experimental analyses in literature, artificial neural networks (ANNs) are probable to have a great latent to expose cost structures by machine learning (ML). This study presents a novel Interpretation of Kernel Regression Neutrosophic Set using Enhanced Coati Optimization for Cost Estimation Model (KRNSECO-CEM). The main goal of the presented KRNSECO-CEM technique is to analyze and interpret the multi-product of Supply Chain Management Systems. At first, the KRNSECO-CEM approach applies Z-score normalization to pre-process the input data. For the regression process, the kernel regression based neutrosophic set (KRNS) model can be used. Eventually, the enhanced coati optimization algorithm (ECO) has been applied for the fine-tuning of the best hyperparameter of the KRNS model. The experimental evaluation of the KRNSECO-CEM algorithm can be tested on a benchmark dataset. The extensive outcomes highlighted the significant solution of the KRNSECO-CEM approach over other recent approaches

**Keywords:** Supply Chain Management; Enhanced Coati Optimization; Neutrosophic Set; Intuitionistic Fuzzy Set; Kernel Regression

## 1. Introduction

One of the most effective devices to model uncertainties in decision-making difficulties is the neutrosophic set (NS) and its growth-like interval complex NS (ICNS), complex NS (CNS), and interval NS (INS) [1]. The well-organized tool to demonstrate vagueness and uncertainty in decision-making symbolizes NS that can be more commonly of an intuitionistic fuzzy set (IFS), classical set, and fuzzy set in addition to 3 classifies of

indeterminacy, falsehood, and truth of a definite statement [2]. It is used in different decision-making procedures. However, for adapting NS to more actual composite cases, INS and CNS are suggested consequently [3]. A supply chain (SC) is a combined method where different business things (for example: manufacturers, suppliers, retailers, and distributors) work together to obtain raw components or materials, change these raw components or materials into particular finished products, and distribute these finished products to distributors [4]. This chain has been conventionally considered in the materials flow and information both between and inside commercial bodies. SC management represents the application of information technology for providing automatic intellect of the control and planning of the SC flow for speeding time to market, reducing inventory stages, lowering complete costs, and, finally, improving customer satisfaction and service [5]. SC management is a complex process, thus keeping productiveness flow efficiently and focusing on the worst areas within a chain, where every time there is a space for development has been important [6]. Machine Learning (ML) is a technique that can be related to the application and development of computing methodology that learns from knowledge [7]. ML made of the increasing capacity across the past dual decades machineries can manage vast information input, and some technologies can still find unseen patterns and composite relations to create reliable and proper results where humans cannot, particularly for discontinuous and disruptive information [8]. The work exposed that mechanisms can offer more precise outcomes than humans in numerous areas of decision-making can and take place when they are replaced [9]. An intellectual simulation method in the SC is constructed with fusion-based techniques and ML methods to expose the outcomes [10].

This study presents a new Interpretation of the Kernel Regression Neutrosophic Set using enhanced coati optimization for the Cost Estimation Model (KRNSECO-CEM). At first, the KRNSECO-CEM approach applies Z-score normalization to pre-process the input data. For the regression process, the kernel regression based neutrosophic set (KRNS) model can be used. Eventually, the enhanced coati optimization algorithm (ECO) has been applied for the fine-tuning of the best hyperparameter of the KRNS model. The experimental evaluation of the KRNSECO-CEM algorithm can be tested on a benchmark dataset.

## 2. Literature Review

Chien et al. [11] presented an analysis associated with research concerned with the decision elements of the presented PDCCCR method and considered the impact relationships between capacity portfolio, demand planning, pricing, and cost structures for complete financial restoration to develop the effects for intelligent manufacturing. Consequently, a decision method can be presented to incorporate cooperative decisions for worldwide welfare and everyday suggestions. Shabani Khfari et al. [12] presented an article on Supply Chain Cost to predict a method of management dashboard designs for estimation of supply chain costing, concentrating on quantitative methods and prediction. Oriji and Joel [13] present the incorporation of accounting methods with SCM in the aerospace industry as a tactical method for improving efficacy and decreasing costs in the United States. The aerospace industry confronts various challenges, containing intricate stringent regulatory requirements, cost pressures, and supply chains.

Jana [14] presented the dual impacts of uncertain interval SCV and SCR on the efficacy of the SCM were examined in this study. In this research, 2 various methods specifically the CC model and the EV model utilizing the uncertain interval programming methods are advanced. Malik et al. [15] presented coordination in a 2 SC member with a flexible production system under the buyer's stochastic demand and service level restraint. The research implements a various examination strategy and uses discrete investing functions for the reduction of system costs. Negotiating is the important focus of any business at present in the SC players to gain from a collaborative central method. Saha [16] proposes a concentrated study of a small pizza shop under the conditions that contain the loss of suppliers, delays, and employees, and studied the improved cost of supplies. A predicting workflow simulation method and supply chain utilizing the SIMIO software has been generated to assess the impacts of fine-tuning switching replenishment and shift resources tactics. This study aimed to assist and identify the optimum resource allocation at every workplace based on utilization and availability. Zahraee et al. [17] introduce a combined geographical information system and agent based simulating model tool to fill this knowledge gap. The 2 major systems of land goods truck and train, with 3 dimensions of capability (medium, heavy, and light) are assessed for the research.

## 3. Materials and Methods

In this article, we have designed a new Interpretation of the KRNSECO-CEM model. The main goal of the presented KRNSECO-CEM technique is to analyse and interpret the multi product of Supply Chain Management Systems. To accomplish that, the developed KRNSECO-CEM model involves data preprocessing, regression process, and hyperparameter tuning method. Fig. 1 represents the overall workflow of KRNSECO-CEM technique.

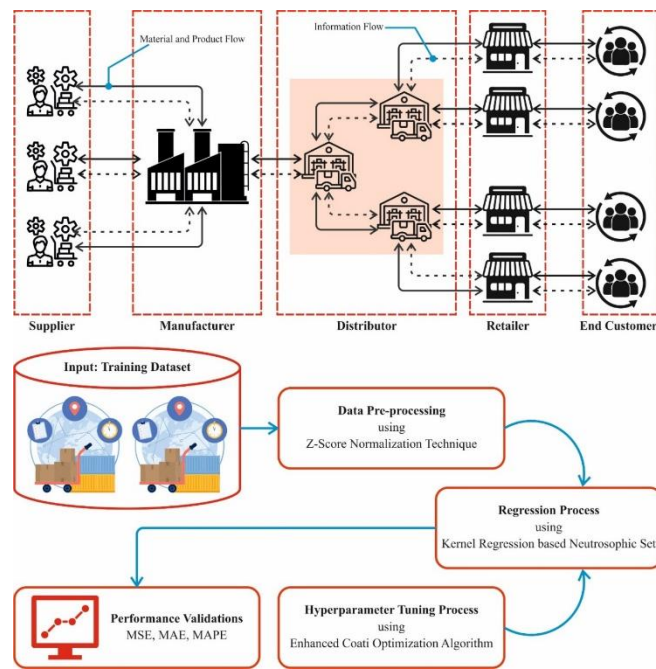


Figure 1. Workflow of KRNSECO-CEM technique

**A. Data Preprocessing**

At first, the KRNSECO-CEM approach applies Z-score normalization to pre-process the input data. Z-score normalization is a method, employed to regulate data by altering it into a usual measure with a mean of zero and a standard deviation of one [18]. In the perspective of cost estimation for multi-product SCM systems, Z-score normalization aids in equating and combining cost data through dissimilar processes and products. By eliminating scaling and units, it certifies that variants in cost owing to diverse dimension scales do not twist the analysis.

**B. KRNS-based Regression Process**

Furthermore, for the process of regression, the KRNSECO-CEM algorithm employs the KRNS system. The theory of NS is derived from a novel philosophy branch such as neutrosophy [19]. It obtained popularity due to its ability to handle the nature, origin, and neutralities scope, along with their communications through various spectral conceptions.

Definition 2.1.1: Let  $E$  remain points space (objects) with a generic  $E$  element represented as  $y$ . Formerly, an NS  $Nl$  in  $E$  can be considered by membership functions of truth  $T_{N1}$ , an indeterminacy  $I_{N1}$  and a falsity  $F_{N1}$ . These functions  $T_{N1}$  and  $F_{N1}$  are non-standard or real standard subdivisions of  $[0, 1^+]$  that is  $T_{N1}: E \rightarrow [-0, 1^+]; I_{N1}: E \rightarrow ]-0, 1^+; F_{N1}: E \rightarrow ]-0, 1^+]$ .

It must be observed that there are no limits to the sum of  $T_{N1}(y)I_{N1}(y)F_{N1}(y)$  i.e.

$$-0 \leq T_{N1}(y) + I_{N1}(y) + F_{N1}(y) \leq 3^+$$

Definition 2.1.2: (complement) The NS complement  $A$  can be signified by  $NI^c$  and has been described by

$$T_{N1}^c(y) = \{1^+\} - T_{N1}(y); I_{N1}^c(y) = \{1^+\} - I_{N1}(y)$$

$$F_{N1}^c(y) = \{1^+\} - F_{N1}(y)$$

Definition 2.1.3: (Containment) A NS  $Nl$  are enclosed in the additional NS  $N2$ ,  $Nl \subseteq N2$  assuming that the succeeding outcome holds.

$$\inf T_{N1}(y) \leq \inf T_{N2}(y), \sup T_{N1}(y) \leq \sup T_{N2}(y)$$

$$\inf I_{N1}(y) \geq \inf I_{N2}(y), \sup I_{N1}(y) \geq \sup I_{N2}(y)$$

$$\inf F_{N1}(y) \geq \inf F_{N2}(y), \sup F_{N1}(y) \geq \sup F_{N2}(y) \text{ for all } y \text{ in } E.$$

Definition 2.1.4: (Single-valued NS).

Let  $E$  stand global points space (objects) with a generic  $E$  element signified as  $y$ .

A single valued NS  $S$  can be considered by membership functions of truth  $T(y)$ , falsity  $FN(y)$ , and an indeterminacy  $IN(y)$  with  $TN(y), FN(y), IN(y) \in [0,1]$  for all  $y$  in  $E$ .

After  $E$  is constant, an SNVS  $S$  is transcribed in the following:

$$s = \int_y \langle T_S(y)_{F_S(y)} I_S(y) \rangle / y, \forall y \in E$$

And after  $E$  is distinct, an SVNS  $S$  is composed below:

$$s = \Sigma \langle T_S(y)_{F_S(y)} I_S(y) \rangle / y, \forall y \in E$$

It ought to be noticed that for an SVNS  $S, 0 \leq \sup T_S(y) + \sup F_S(y) + \sup I_S(y) \leq 3, \forall y \in E$

Definition 2.1.5: (Intersection) The dual intersection SVNSs  $N1$  and  $N2$  an SVNS  $N3$ , entered as  $N3 = N1 \cap N2$ . Its falsity, indeterminacy, and truth membership functions are linked with  $N1$  and  $N2$  as below:

$$T_{S_{N3}}(y) = \min(T_{S_{N1}}(y), T_{S_{N2}}(y));$$

$$I_{S_{N3}}(y) = \max(I_{S_{N1}}(y), I_{S_{N2}}(y));$$

$$F_{S_{N3}}(y) = \max(F_{S_{N1}}(y), F_{S_{N2}}(y)), \forall y \in E.$$

Distance between dual NS. The overall SVNS is offered in the subsequent procedure

$$S = \{ (y / (T_S(y), I_S(y)_{F_S(y)})) : y \in E \}$$

Limited SVNSs are signified below:

$$S = \left\{ \begin{matrix} (y_1 / (T_S(y_1)_{I_S(y_1)_{F_S(y_1)}})), \dots \\ (y_m / (T_S(y_m)_{I_S(y_m)_{F_S(y_m)}})) \end{matrix} \right\}, \forall y \in E \tag{1}$$

Definition 2.1.6: Let be dual single-valued NS, formerly the hamming distance among dual SNVS  $N1$  and  $N2$  is classified below:

$$S_{N1} = \left\{ \begin{matrix} (y_1 / (T_{S_{N1}}(y_1), I_{S_{N1}}(y_1), F_{S_{N1}}(y_1))), \dots, \\ (y_n / (T_{S_{N1}}(y_n), I_{S_{N1}}(y_n), F_{S_{N1}}(y_n))) \end{matrix} \right\} \tag{2}$$

$$S_{N2} = \left\{ \begin{matrix} (x_1 / (T_{S_{N2}}(y_1), I_{S_{N2}}(y_1), F_{S_{N2}}(y_1))), \dots, \\ (x_n / (T_{S_{N2}}(y_n), I_{S_{N2}}(y_n), F_{S_{N2}}(y_n))) \end{matrix} \right\} \tag{3}$$

$$d_S(S_{N1}, S_{N2}) = \sum_{i=1}^n ( |T_{S_{N1}}(y) - T_{S_{N2}}(y)| + |I_{S_{N1}}(y) - I_{S_{N2}}(y)| + |F_{S_{N1}}(y) - F_{S_{N2}}(y)| ) \tag{4}$$

Normalizing the hamming distance amongst dual SNVSs  $S_{N1}$  and  $S_{N2}$  can be distinguished in this way:

$$Nd_S(S_{N1}, S_{N2}) = \frac{1}{3n} \sum_{i=1}^n ( |T_{S_{N1}}(y) - T_{S_{N2}}(y)| + |I_{S_{N1}}(y) - I_{S_{N2}}(y)| + |F_{S_{N1}}(y) - F_{S_{N2}}(y)| ) \tag{5}$$

with the succeeding possessions

$$0 \leq d_S(S_{N1}, S_{N2}) \leq 3n \tag{6}$$

$$0 \leq Nd_S(S_{N1}, S_{N2}) \leq 1 \tag{7}$$

A model based neutrosophic predicting estimation of the population mean via (Gaussian) kernel regression is presented [20]. That is noted that each investigation endeavors concentrate on using accurate, efficient data for the prognostic population mean estimation in a sampling survey. We have intended to find a precise estimation for the unidentified population value while minimalizing the mean square error (MSE). The statement is that the population of neutrosophic is sensibly defined in the neutrosophic predictive method  $\zeta_N$ .

$$y_{iN} = m(x_{iN}) + \varepsilon_{iN} \tag{8}$$

Now  $\varepsilon_{iN}$  are autonomous and equally distributed with  $E_{\zeta}(\varepsilon_{iN}) = 0$ , with constant variance  $\sigma^2$ . The  $m$  represents the neurosophic variant smoothing function  $x_{iN}$ .  $E_{\zeta}$  signify the predictable value concerning the method, normally termed the expectation of the model. When the sample observation from the population of neurosophic has occurred, the estimator  $\bar{Y}_N$  includes making any predictions depending on unobserved function values  $Y_N$ . The intention is to approximate the unknown population mean that is formulated below:

$$\bar{Y}_N = f\bar{y}_{sN} + (1 - f)\bar{y}_{\bar{s}N} \tag{9}$$

Here,  $\bar{y}_{sN} = \frac{1}{n} \sum_{i \in s} y_{iN}$  and  $\bar{y}_{\bar{s}N} = \frac{1}{N-n} \sum_{j \in \bar{s}} y_{jN}$ . Further,  $\bar{y}_{sN} \in [\bar{y}_{sL}, \bar{y}_{sU}]$  and  $\bar{y}_{\bar{s}N} \in [\bar{y}_{\bar{s}L}, \bar{y}_{\bar{s}U}]$ .  $i$  symbolizes the units inside the model  $s$  and  $j$  signifies the values within the  $\bar{s} = U - s$ . Additionally,  $U$  characterizes a neurosophical population. During Eq. (9), the original element is acknowledged before, and the  $\bar{Y}_N$  the estimation includes the mean prediction  $\bar{y}_{\bar{s}N}$  within the data which cannot be the sample part. While the  $x_N$  values are obtainable for the complete population, a normally applied model for claiming predictions is to utilize a regression technique that deliberates the proxy  $y = m(x_{jN})$  values as predictions for the unnoticed values  $y_{jN}$ , whereas  $j \in \bar{s}_N$ . When the  $m(x_{jN})$  values familiar, an  $\bar{Y}_N$  estimator is

$$\bar{y}_{pN} = f\bar{y}_{sN} + (1 - f)\frac{1}{N-n} \sum_{j \in \bar{s}} y_{jN}^0 \tag{10}$$

In an applied setting the  $m(x_{jN})$  values are unknown. Therefore the estimator applicability exposed in Eq. (10) is problematic. Let  $K_{hN}(u) = h^{-1}K_N\left(\frac{u}{h}\right)$ , given that,  $K_N$  signifies the neurosophic constant function of the symmetrical (Gaussian) kernel and  $h$  signifies the bandwidth in that context. Therefore, a consistent prediction for the unidentified  $m(x_{jN})$  has been gained from

$$\hat{m}_{jN} = e_1'(X'_{sjN}W_{sjN}X_{sjN})^{-1}X'_{sjN}W_{sjN}Y_{sN} = W_{sjN}^- Y_{sN} \tag{11}$$

In Eq.(3),  $e_1 = (1, 0, \dots, 0)'$  signifies a column vector using a +1length,  $Y_{sN} = [y_L, y_U]$ ,  $W_{siN} = \text{diag}\left(K_h(x_{iN} - x_{iN})\right)$  whereas  $j \in s$ ,  $x_{iN} \in [x_{iL}, x_{iU}]$ ,  $x_{iN} \in [x_{jL}, x_{jU}]$ ,  $W_{siN} = [W_{sjL}, W_{sjU}]$  and  $X_{siN} = [1, (x_{iN} - x_{iN}, \dots, (x_{iN} - x_{iN})^p)]$  while  $i \in s$ . Here,  $j \in \bar{s}$  for that  $X_{sjN} \in [X_{sL}, X_{sU}]$ . By integrating Eq. (11) in Eq.(10), the neurosophic local polynomial regression estimator for the population mean can be definite in the following,

$$\bar{y}_{MBN} = f\bar{y}_{sN} + (1 - f)\frac{1}{N-n} \sum_{j \in \bar{s}} \hat{m}_{jN} \tag{12}$$

Now,  $\bar{y}_{sN} = \frac{1}{n} \sum_{i \in s} y_{iN}$  for which  $\bar{y}_{sN} \in [\bar{y}_{sL}, \bar{y}_{sU}]$ ,  $U$  and  $L$  represent upper and lower values correspondingly. Additionally,  $f = n/N$  and  $\hat{m}_{jN} = e_1'(X'_{siN}W_{siN}X_{siN})^{-1}X'_{siN}W_{siN}Y_{sN} = W_{siN}' Y_{sN}$ . The terms utilized in  $\hat{m}_{jN} \in [\hat{m}_{jL}, \hat{m}_{jU}]$  are previously designated in former outlines.

### C. ECOA-based Hyperparameter Tuning Method

At last, the ECOA has been applied for the fine-tuning of the best hyperparameter of the KRNS model. COA is a novel metaheuristic model [21]. In  $P$ - dimensionality space, every coati performs like an isolated search individual. The coati's hunting and escaping manner from predators are both individually updated. The coati location should be adapted dynamically based on the iguana's placement and the traveled locations, and lastly, the best candidate solution (the globally optimal location) should be preferred. Then, we would concisely present the mathematical COA model.

#### i) Process of Initialization

Initially, the COA starts  $m$  randomly formed individuals,  $x_1, \dots, x_i, \dots, x_m$ , in Eq.(13), whereas the maximal limit for individual values is  $X_{\max} = (x_1^{\max}, \dots, x_p^{\max})$  and the minimal boundary is  $X_{\min} = (x_1^{\min}, \dots, x_p^{\min})$ . Formerly, assess the initialized randomly formed individuals over the objective function.

$$x_{i,j} = x_j^{\min} + \text{rand} \cdot (x_j^{\max} - x_j^{\min}), i = 1, 2, \dots, m, j = 1, 2, \dots, p. \tag{13}$$

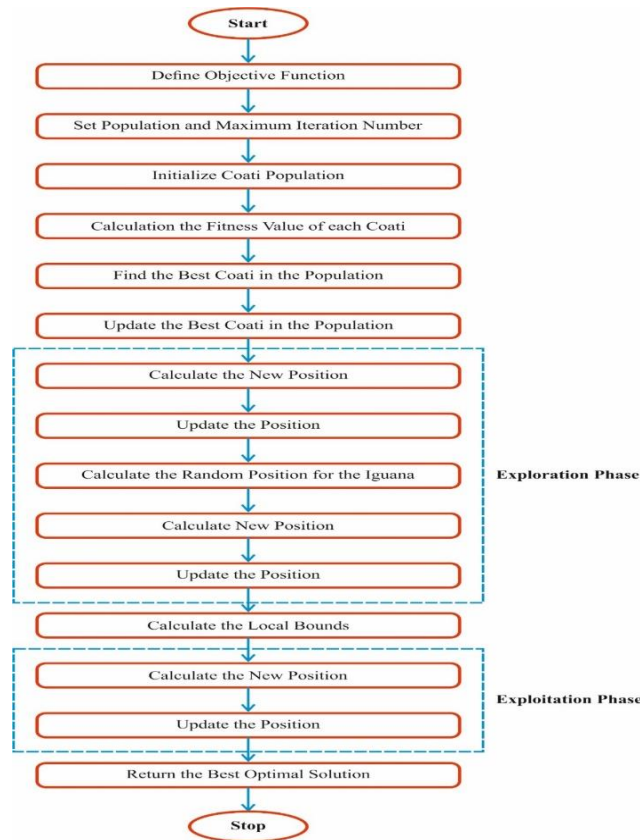


Figure 2. Flowchart of ECOA method

ii) Exploration stage (Attack and Hunting Strategies)

Coatis attacking iguanas in collections. In this approach, the coatis are initially separated into dual clusters. Some sets climb a tree to scare and approach the iguana, whereas the other set waits unobtrusively on ground level.

$$x_{i,j}^{new} = x_{i,j} + b \cdot (Igu_j - I \cdot x_{i,j}), i = 1, 2, \dots, \lfloor \frac{m}{2} \rfloor. \quad (14)$$

Once the iguana is scared to place, the iguana location is randomly arranged; but, the other half coatis waiting on the ground moves based on the iguana’s random position. This behavior can be signified in Eqs. (15) and (16).

$$Igu_j = x_j^{min} + b \cdot (x_j^{max} - x_j^{min}), j = 1, 2, \dots, p, \quad (15)$$

$$x_{i,j}^{new} = \begin{cases} x_{i,j} + b \cdot (Igu_j - I \cdot x_{i,j}), & F_{Igu} < F_i \\ x_{i,j} + b \cdot (x_{i,j} - Igu_j), & F_{Igu} > F_i \end{cases}, i = \lfloor \frac{N}{2} \rfloor + 1, \lfloor \frac{N}{2} \rfloor + 2, \dots, N, j = 1, 2, \dots, m, \quad (16)$$

Here  $x_{i,j}$  denotes the  $j$ -th size of the  $i$ -th coati, and  $b$  represents stochastical numbers among [0,1].  $Igu$  signifies the location given at random of the iguana.  $I$  is some stochastical values within 1 and 2.

iii) The Exploitation Stage (Stage of Escaping Predators)

In the growth stage, the tactic accepted by the coati in escaping and facing hunters is employed to upgrade its location. After a hunter catches a coati, it rapidly moves and enters a quite safer location, coming close to the best place. These strategies determine the ability of the COA model’s growth. Eqs can replicate the tactic in the growth stage. (17) and (18).

$$low_j = \frac{x_j^{min}}{t}, up_j = \frac{x_j^{max}}{t}, t = 1, 2, \dots, T, \quad (17)$$

$$x_{i,j}^{new} = x_{i,j} + (1 - 2b) \cdot (low_j + b \cdot (up_j - low_j)), i = 1, 2, m, j = 1, 2, p \quad (18)$$

Now  $up_j$  and  $low_j$  specify the local upper and lower limit of the  $j$ -th size, a stochastical number through a  $b$  value between [0,1]. If the upgrade accepted coati’s value is better than the original accepted value, the value has been adopted; then, must not take these values. Eq. (19) denotes the process of update.

$$X_i = \begin{cases} X_i^{new}, F_i^{new} < F_i \\ X_i, else \end{cases} \tag{19}$$

The Conventional COA accepts the process of the initial population positioning at random, which can be problematic for spreading during the population, subsequent in a diversity lacking in the new population of coati and limiting the resilience Chaos mapping has been presented initially. Chaos mapping has features like traversal, regularity, and randomness. These strategies can ensure the original population diversity. They used the chaotic mapping technique to reinforce the sparrow optimization algorithm. The chaos concept mostly investigates the dynamical behavior methods, which are complex in early phases. The process of making an original population over chaotic mapping is to initially apply a 1-D chaotic mapping, identify a randomly generated primary values in it, and iteratively make a sequence of constant points. Chaotic mapping tactics can increase the capability of convergence, success rate, and population diversity. Fig. 2 represents the flowchart of the ECOA method. In this study, the ECOA is utilized to identify the hyperparameter engaged in the KRNS method. The MSE is measured as the objective function and can be identified below.

$$MSE = \frac{1}{T} \sum_{j=1}^L \sum_{i=1}^M (y_j^i - d_j^i)^2 \tag{20}$$

Where  $M$  and  $L$  signify the resulting value of layer and data consistently,  $y_j^i$  and  $d_j^i$  means the achieved and proper magnitudes for  $j^{th}$  unit from the resulting layer of the network in time  $t$  respectively.

#### 4. Experimental Result and Analysis

This section studies the performance analysis of the KRNSECO-CEM method utilizing the Supply Chain dataset [22]. Fig. 3 establishes the correlation matrix created by the KRNSECO-CEM method. The results state that the KRNSECO-CEM technique has an effective prediction of all classes precisely.

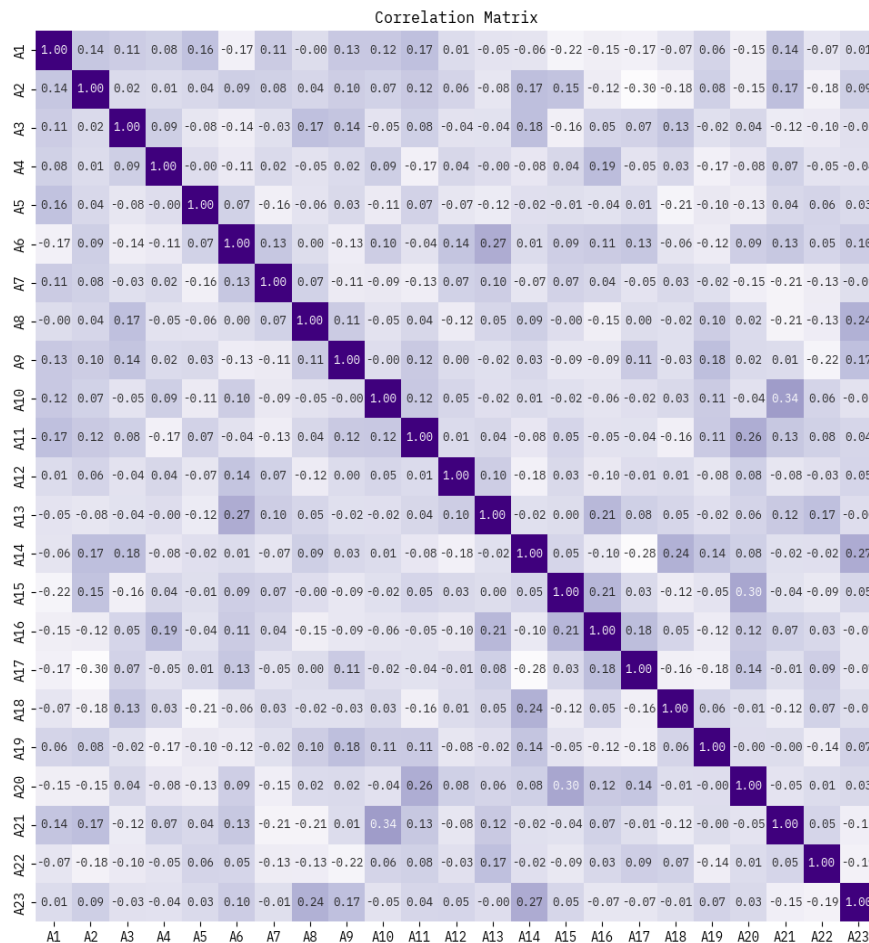
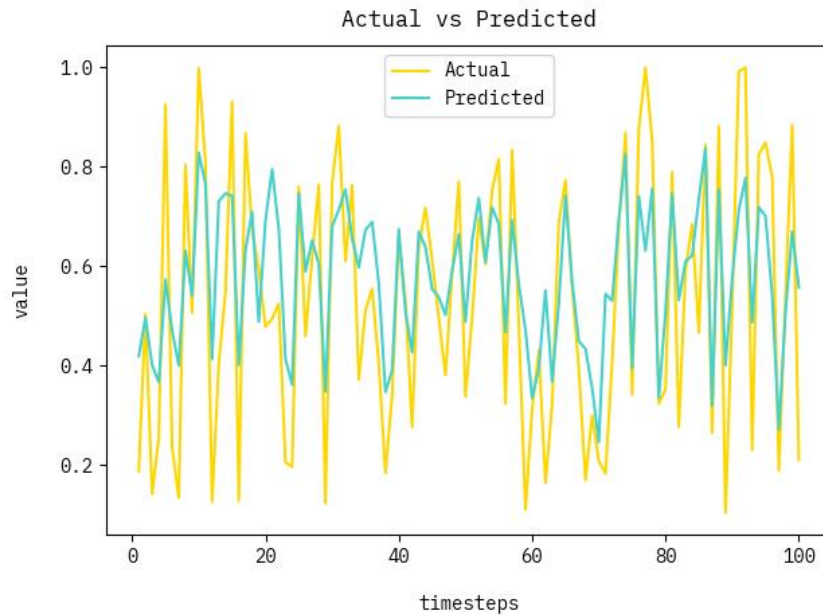
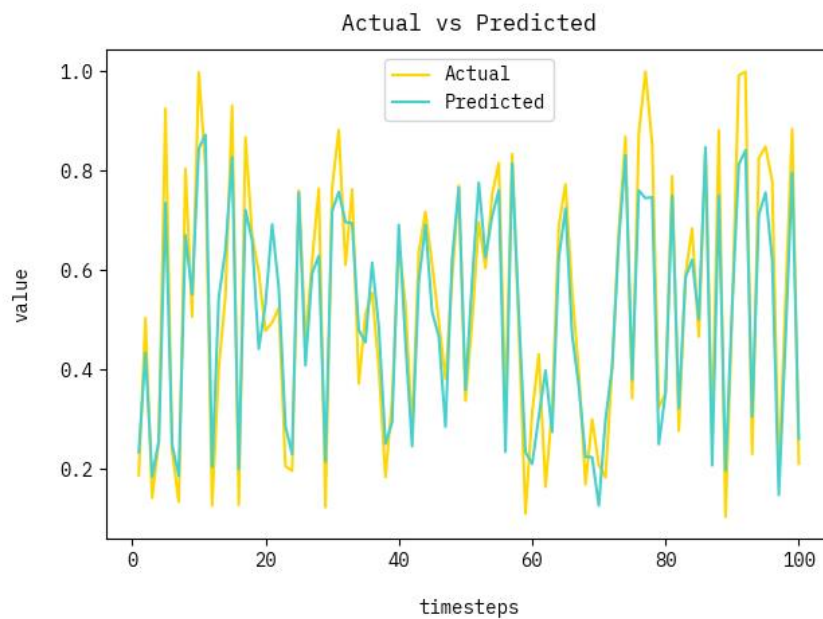


Figure 3. Correlation matrix of KRNSECO-CEM technique

Fig. 4 distributes an outcome study for the actual vs prediction of the KRNSECO-CEM approach under Epoch 25. The results represented that the KRNSECO-CEM technique has enhanced prediction results. The figure shows the actual vs. prediction outcomes of the KRNSECO-CEM process. The results indicated that the KRNSECO-CEM system has exposed enhanced predicted outcomes under every hour of operation. It is also well known that the variance between the predicted and actual values is measured at the least.

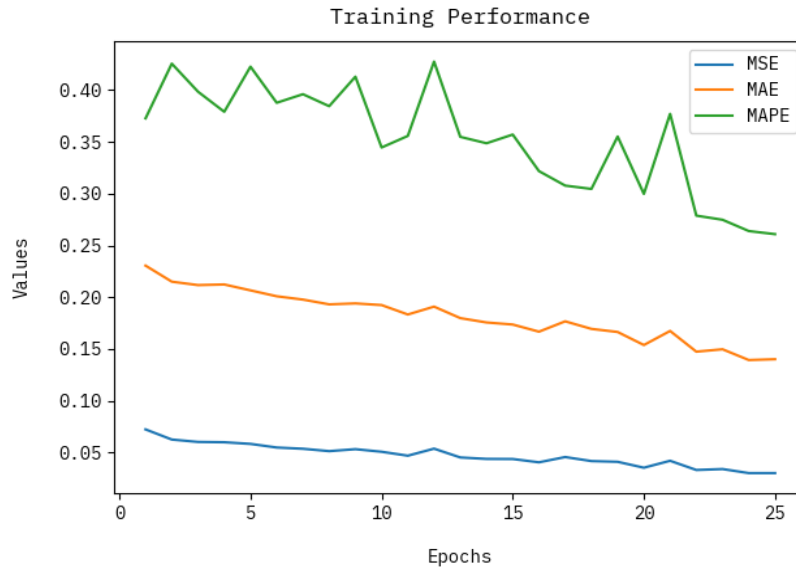


**Figure 4.** Results Analysis for Actual vs Prediction Graph of KRNSECO-CEM technique under Epochs 25



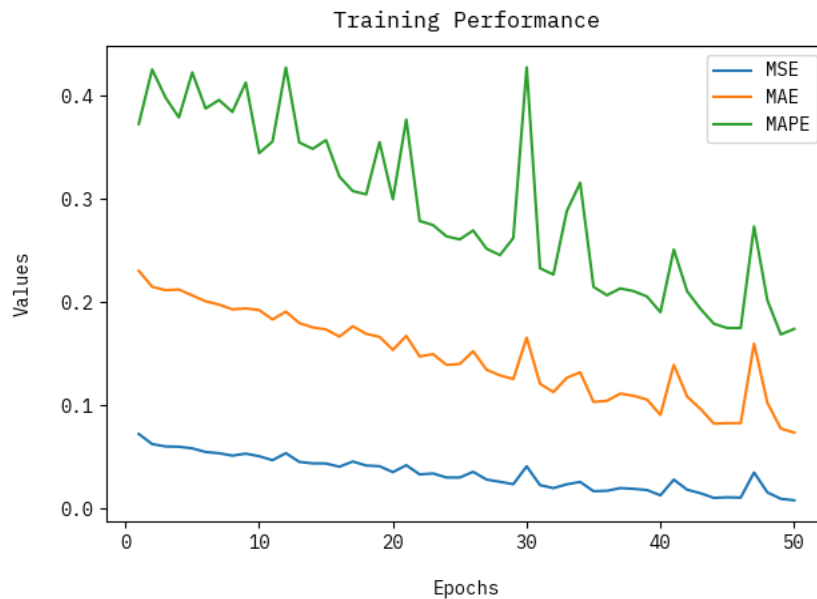
**Figure 5.** Results Analysis for Actual vs Prediction Graph of KRNSECO-CEM technique under Epochs 50

Fig. 5 distributes a result study for actual vs prediction of the KRNSECO-CEM method under Epoch 50. The outcomes demonstrated that the KRNSECO-CEM approach has improved prediction outcomes. The figure shows the actual vs. prediction outcomes of the KRNSECO-CEM process. The results indicated that the KRNSECO-CEM model has exposed enhanced predicted outcomes under every hour of operation. It is also well known that the variance between the predicted and actual values is measured at the least.



**Figure 6.** Performance Analysis for Loss Graph of KRNSECO-CEM technique under Epochs 25

Fig. 6 established the performance study for the loss graph of the KRNSECO-CEM technique under epoch 25. The loss values are computed for 0-25 epochs. It is denoted that the training values indicate the lowest trend, notifying the ability of the KRNSECO-CEM process to balance a trade-off between data fitting and generalization. The continual reduction in loss values additionally guarantees the enhanced performance of the KRNSECO-CEM approach and tunes the prediction results over time.



**Figure 7.** Performance Analysis for Loss Graph of KRNSECO-CEM technique under Epochs 50

Fig. 7 established performance analysis for the loss graph of the KRNSECO-CEM process under epoch 50. The loss values are computed for 0-50 epochs. It is denoted that the training values show a lesser trend, notifying the ability of the KRNSECO-CEM approach to balance a trade-off between data fitting and generalization. The continual reduction in loss values additionally guarantees the enhanced performance of the KRNSECO-CEM technique and tunes the prediction results over time.

Table 1 and Fig. 8 represent the classification results of the KRNSECO-CEM process with distinct metrics. The outcomes inferred that the KRNSECO-CEM model has attained an MSE of 0.008. Likewise, the KRNSECO-CEM approach has obtained an MAE of 0.074. Eventually, the KRNSECO-CEM methodology obtained a MAPE of 0.174.

**Table 1:** Classifier outcomes of KRNSECO-CEM technique with distinct metrics

Metrics	Values
MSE	0.008
MAE	0.074
MAPE	0.174

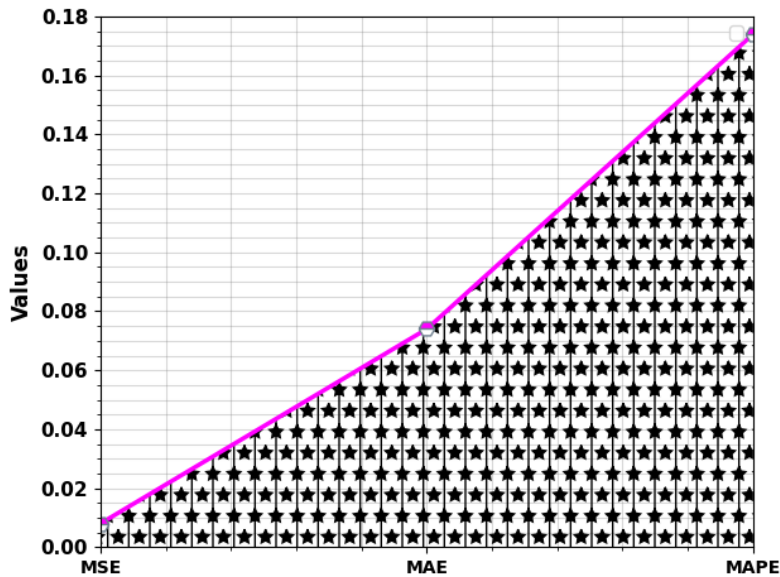


Figure 8. Average of KRNSECO-CEM technique with distinct metrics

To show the proficiency of the KRNSECO-CEM method, a detailed comparison study is made in Table 2 and Fig. 9. The experimental values inferred that the KRNSECO-CEM model has better performances in terms of MSE. The Random Forest model has displayed poor performances with a higher value MSE of 0.020. At the same time, the Lasso Regression model has obtained a slightly lesser MSE of 0.017. Meanwhile, the SVR, Decision Tree, and Linear Regression models have illustrated closer values MSE of 0.016, 0.013, and 0.011, respectively. Nevertheless, the KRNSECO-CEM approach outcomes in improved performance with a lower value of MSE of 0.008. Therefore, the KRNSECO-CEM system can be utilized for analyzing and interpreting cost estimation.

Table 2: MSE outcome of KRNSECO-CEM technique with existing approaches

Classifiers	MSE
KRNSECO-CEM	0.008
Linear Regression	0.011
Decision Tree	0.013
SVR Model	0.016
Lasso Regression	0.017
Random Forest	0.020

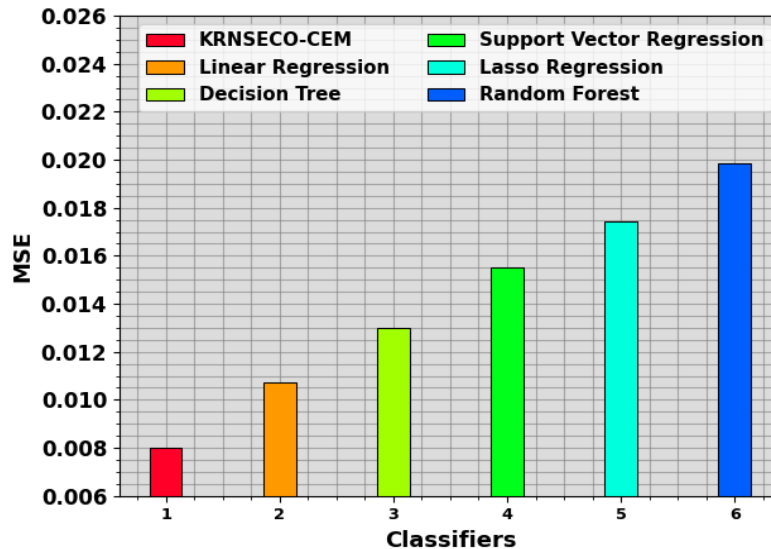


Figure 9. MSE outcome of KRNSECO-CEM technique with existing approaches

## 5. Conclusion

In this article, we have designed a new Interpretation of the KRNSECO-CEM technique. The main goal of the presented KRNSECO-CEM technique is to analyse and interpret the multi-product of SCM Systems. To accomplish that, the developed KRNSECO-CEM model involves data pre-processing, regression process, and hyperparameter tuning method. At first, the KRNSECO-CEM approach applies Z-score normalization to pre-process the input data. For the regression process, the KRNS model can be used. Eventually, the ECOA has been applied for the fine-tuning of the best hyperparameter of the KRNS model. The experimental evaluation of the KRNSECO-CEM algorithm can be tested on a benchmark dataset. The extensive outcomes highlighted the significant solution of the KRNSECO-CEM approach over other recent approaches.

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