Pentapartitioned Neutrosophic Vague Soft Set with Optimization Algorithm Based Business Intelligence Framework for Data-Driven Demand Forecasting Model

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Abstract

Neutrosophic logic is a neonate research field in which all propositions are anticipated to have the percentage (proportion) of truth in a sub-set T, the proportion of falsity in a sub-set F, and the proportion of indeterminacy in a sub-set I. Neutrosophic set (NS) is efficiently applied for indeterminate information processing and provides assistance to address the indeterminacy information of data. Demand Forecasting, undoubtedly, is the only most significant element of some organization's Supply Chain. It defines the predictable demand for the future and sets the preparedness level that is needed on the supply side to match the demand. Business intelligence (BI) plays a significant part in helping the decision maker obtain the understanding for increasing productivity or improved and faster decisions. Furthermore, it improves and helps the efficacy of functional rules and its influence on corporate-level decision-making that provides improved strategic options in dynamic business environments. Within the period of data-driven demand forecasting, the integration of artificial intelligence (AI) technologies in BI models has transformed the system groups that utilize and analyze data. In the manuscript, a Business Intelligence Framework for a Data-Driven Demand Forecasting Model Using a Pentapartitioned Neutrosophic Vague Soft Set (BIFDDF-PNVSS) technique is proposed. The main goal of the BIFDDF-PNVSS technique is to progress the accurate BI structure for the demand forecasting method. The data pre-processing stage is initially applied for converting input data into a beneficial format by the Z-score normalization method. Moreover, the PNVSS technique is utilized for the data-driven demand prediction model. Finally, to improve the prediction performance of the PNVSS model, the parameter tuning process is performed by implementing the cheetah optimization algorithm (COA) model. A comprehensive experimentation is performed to verify the performance of the BIFDDF-PNVSS methodology under the demand forecasting dataset. The BIFDDF-PNVSS methodology outperforms existing techniques with a superior MSE of 0.0008, demonstrating its exceptional accuracy in demand forecasting compared to other models.

Keywords: Business Intelligence; Neutrosophic Logic; Pentapartitioned Neutrosophic Vague Soft Set; Fuzzy Set; Data Driven Demand Forecasting

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1. Introduction

The idea of the NS is from a logical opinion, which is an overview of the idea of fuzzy set (FS) and IFS [1]. An NS is categorized by indeterminacy, truth, and falsity. Every membership degree is an actual benchmark or a non-actual benchmark subset of the non-actual unit interval [−0, 1+]. In contrast with IFSs, there are no restrictions on the membership functionality in an NS, and a degree of hesitance was involved in the NS [2]. However, NS is tough to use in real-world difficulties meanwhile the truth-values, indeterminacy, and falsity membership functionality lie in [−0, 1+]. Hence, these concepts have been expanded to many NS by which truth, falsity, and indeterminacy membership functionalities took single values within the closed interval [0, 1]. BI denotes a set of practices, applications, and technologies that are intended to collect, present, and analyse business information in a significant manner [3]. The BI tool aids businesses in processing huge amounts of information and converting it into actionable visions that will update strategic resolutions. This vision may comprise market conditions, trend forecasting, historical performance analysis, and customer behaviour where each of them is significant to improve the operations of the business [4]. BI platform classically utilizes a diversity of tools, which includes dashboards, advanced analytics, data visualization, and reporting for making understandable and available information to both nontechnical and technical shareholders. By giving a complete summary of the performance of a business, BI permits organizations in order to classify opportunities, mitigate risks, and streamline operations [5].

Demand Forecasting is an important activity that roughly manages every other activity of supply chain management (SCM) [6]. It is a vital aspect of decision-making and planning in both BI and SCM. Every company relies on the effectiveness of demand forecasting for making significant decisions namely resource allocation, capacity building, forward or backward incorporation and expansion, and so on [7]. Forecasting is an estimation or prediction of real values in an upcoming period. Usually, there may be a forecasting fault as a real outcome varies from the estimated value whereas a long-time horizon has the chances of further faults. It is essential for measuring the forecasting fault to adjust the correct plan of action [8]. The advancement of these technologies allows SCM shareholders to share real-time data and information through the system that supports the double advantage of customer service and inventory. The basic outcome of this procedure is precision in forecasting which strongly safeguards the effective and maintainable operations of the business [9]. The incorporation of AI in BI has revolutionized data-driven demand forecasting, enabling businesses to better comprehend consumer behaviour and predict market trends, and ultimately improving decision-making and competitiveness. This shift allows companies to adjust to changing demands and optimize their strategies for greater efficiency [10].

1.1. Research Motivation for Enhancing Demand Forecasting through BI and AI Integration

The motivation behind incorporating BI with AI in demand forecasting lies in its potential to transform conventional business decision-making processes. As businesses encounter increasingly complex market conditions, the capability to analyse large volumes of data and predict consumer behaviour has become significant. BI gives organizations with the tools to collect, process, and visualize data, assisting to detect opportunities, reduce risks, and optimize operations. AI improves this capability by enabling more accurate forecasting models that adapt to changing market dynamics. Through advanced analytics, businesses can predict trends, comprehend customer behaviour, and make data-driven decisions that enhance strategic planning. This integration presents various merits: enhancing forecasting precision, improving resource allocation, enabling smarter inventory management, streamlining operations, predicting market shifts, increasing competitiveness, giving actionable insights for decision-making, mitigating uncertainty, improving long-term planning, and fostering innovation. Such advancements hold the promise of greater operational efficiency, profitability, and a more dynamic response to evolving consumer demands.

1.2. Study Contribution and Novelty

In the manuscript, a Business Intelligence Framework for a Data-Driven Demand Forecasting Model Using a Pentapartitioned Neutrosophic Vague Soft Set (BIFDDF-PNVSS) technique is proposed. The main goal of the BIFDDF-PNVSS technique is to progress the accurate BI structure for the demand forecasting method. The data pre-processing stage is initially applied for converting input data into a beneficial format by the Z-score normalization method. Moreover, the PNVSS technique is utilized for the data-driven demand prediction model. Finally, to improve the prediction performance of the PNVSS model, the parameter tuning process is performed by implementing the cheetah optimization algorithm (COA) model. A comprehensive experimentation is performed to verify the performance of the BIFDDF-PNVSS methodology under the demand forecasting dataset. The key contribution of the BIFDDF-PNVSS methodology is listed below.

- The BIFDDF-PNVSS model utilizes Z-score normalization for data pre-processing, scaling all features to have a mean of zero and a standard deviation of one. This ensures that the model is less sensitive to outliers and enhances its stability. By standardizing the data, the model attains faster convergence and performance that is more reliable during training.

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- The BIFDDF-PNVSS technique employs the PNVSS model for demand prediction, allowing the model to handle uncertainty and imprecision in the data. This approach improves the capability of the method to make more accurate forecasts by addressing both vagueness and conflicting data. By incorporating PNVSS, the model can provide more reliable predictions in complex and uncertain environments.
- The BIFDDF-PNVSS methodology implements the COA method for parameter tuning, improving the performance of the model by effectually exploring the solution space. The capability of the COA technique to balance exploration and exploitation confirms the discovery of optimal parameters. This optimization process significantly improves the accuracy and overall efficiency of the model during training.
- The novelty of the BIFDDF-PNVSS model is in its unique integration of Z-score normalization, PNVSS for uncertainty handling, and COA for parameter tuning. This integration allows the model to address multiple challenges simultaneously namely data scaling, imprecision, and optimization. By efficiently integrating these advanced techniques, the model attains exceptional accuracy and robustness in demand forecasting, making it highly adaptable to complex real-world scenarios.

2. Literature Survey

Ye et al. [11] developed an innovative universal technique named the time-varying discrete grey method together with a data-driven model structure identification model. Particularly, it projects a universal model from combined polynomial time-varying parameters to combine present discrete grey models. The important assets like affine transformation and unbiasedness. To validate the efficacy of this method, Monte Carlo simulations to evaluate its sturdiness against noise and assess its execution in multi-step-ahead prediction. Orzechowski et al. [12] projected a model for predicting demand at public EV charging stations and employed it to examine the possibility of a data-driven technique to forecast demand. This research projected ML to predict medium-term public EV charging demand to predict demand at various stations. The authors [13] purpose of this analysis is to employ LSTM-NN with hyper-parameter tuning together with a hybrid approach including LSTM and 1-D CNN, to forecast the demand for 8 medicinal drugs. Hassan et al. [14] concentrate on how firms employ the latest instruments in the progression of BI. This study also recommends the MI-DFS for smarter selections in the digital sphere. This model employs the ML model and big data analytics to forecast the upcoming demand for a service or product.

This system gauges the acceptability of BI by managing questionnaires and interviews with service providers and customers. In [15], the prediction of possible demands is predicted with AI is presented. According to the intellectual model, demand estimation is deliberated in the company's major decision-making activity aimed at IHBIM. For demand predictions, initially collected marketing data, and then possible demand for sales or products is forecasted based on necessities employing IHBIM. This prediction depends on data attained from various resources. Muthukalyani [16] inspects the application of AI-driven predictive analytics within the retail supply chain. The major part of AI models like DL and ML methodologies and their capability to investigate huge databases to recognize trends and patterns. Furthermore, the progressive predictive techniques allow retailers to expect demand fluctuations, change the preferences of users, and reduce overstock or stock out situations. Wang [17] employs adaptive NN technology to perform tourism demand prediction analysis. Besides, this study enhances the adaptive NN, thus it can manage several data for tourism demand prediction. Afterwards enhancing the model, this novel utilizes the actual procedure of tourism demand forecast depending on the technology of adaptive NN.

2.1. Limitations and Research Gap in Demand Prediction Models

The limitations of existing studies comprise their inability to effectually handle uncertainty and imprecision in data, a challenge that many methods, comprising LSTM-NN and AI-driven approaches, struggle to address. Many models, such as the time-varying discrete grey method, lack generalizability across diverse datasets, restricting their applicability to specific contexts. Moreover, hybrid models incorporating ML and DL methods often face robustness issues, specifically when dealing with noisy data or making long-term predictions. Existing models excel in short-term forecasting but fail to perform adequately in multi-step-ahead predictions, emphasizing a crucial gap in prediction accuracy. Furthermore, models employing adaptive NN and big data analytics are usually tailored to specific industries, giving limited insight for cross-industry applications. A gap also exists in balancing model accuracy and complexity, as many models prioritize one over the other, neglecting the requirement for simplicity and effectiveness in implementation.

Research Gaps:

- Lack of models that can effectually handle uncertainty and imprecision across diverse domains.
- Limited generalizability of existing models, restricting their usage to specific datasets or industries.
- Insufficient robustness in hybrid models, particularly when predicting over long horizons or with noisy data.
- Inadequate performance in multi-step-ahead demand forecasting, which is significant for long-term decision-making.

- The requirement for models that strike a balance between prediction accuracy and computational complexity for broader applicability.

3. Materials and Methods

In the manuscript, we have developed a novel BIFDDF-PNVSS model. The main intention of BIFDDF-PNVSS technique is to progress the accurate BI structure for the demand forecasting method. It contains three distinct kinds of processes like data normalization, demand forecasting model, and parameter selection.

3.1. Step-by-Step Workflow of the Proposed BIFDDF-PNVSS Model for Demand Prediction

The BIFDDF-PNVSS model follows a well-defined process aimed at attaining superior demand prediction accuracy.

Z-score Normalization for Data Pre-processing: The initial step applies Z-score normalization to scale the data, ensuring uniformity and improving the convergence, stability, and accuracy of the technique.

PNVSS-based Demand Prediction: In this phase, the PNVSS method is utilized to manage uncertainty and imprecision in the data, making it ideal for forecasting demand in complex scenarios.

Parameter Tuning with COA: The final step involves the application of the COA for parameter tuning, which optimizes the performance of the model by effectually searching for optimal hyperparameters.

Each step of the process contributes significantly to the performance of the model, with the integration of normalization, advanced prediction techniques, and optimization ensuring high accuracy and efficiency in demand forecasting.

Fig. 1 depicts the entire flow of the BIFDDF-PNVSS approach.

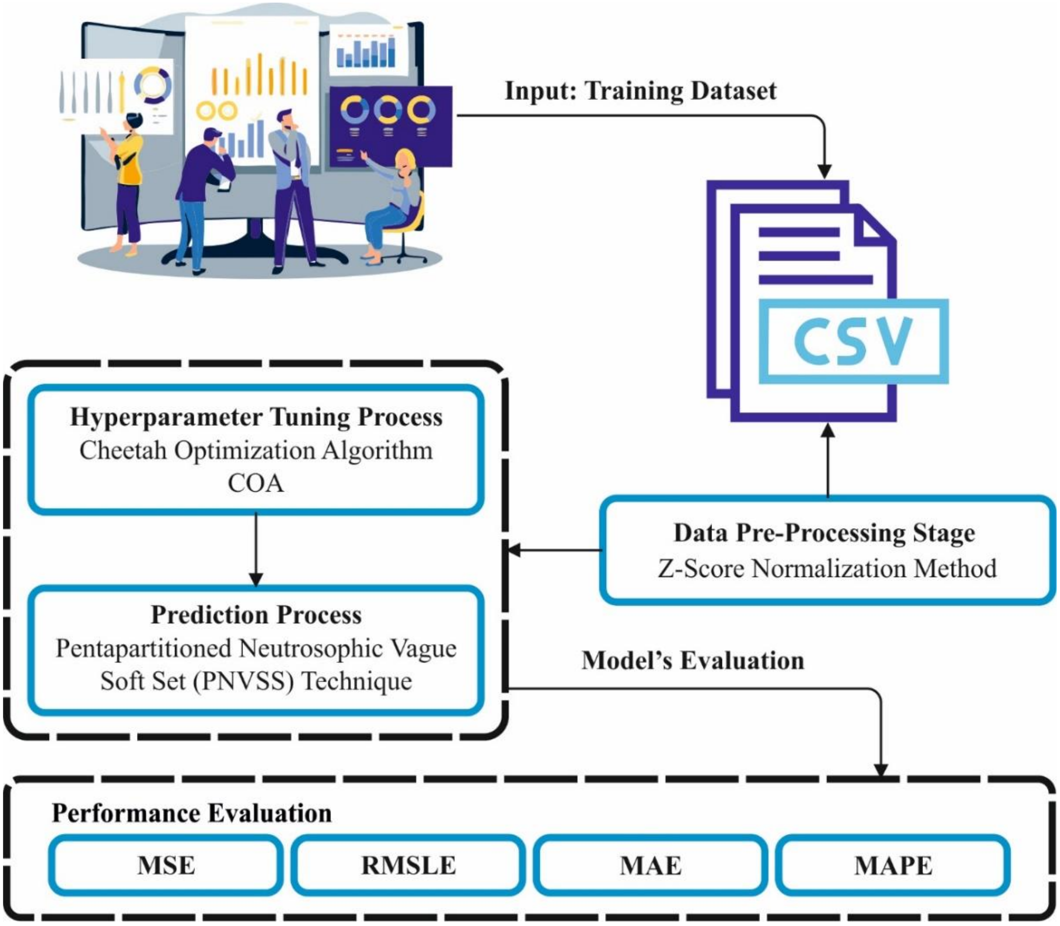

Figure 1. Overall flow of BIFDDF-PNVSS approach

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A. Data Normalization: Z-score

Initially, the data pre-processing stage is applied to transform an input data into a beneficial format by the Z-score normalization method [18]. This model is chosen for its capability to standardize data by transforming features to have a mean of zero and a standard deviation of one. This technique confirms that each feature contributes equally to the model, preventing any one feature from dominating the learning process due to differing scales. It is specifically effectual in scenarios where the data contains outliers or varying units of measurement. Compared to other normalization techniques, namely min-max scaling, Z-score normalization is less sensitive to extreme values, making it more robust. Furthermore, it assists in improving the convergence speed during training, particularly for algorithms like gradient descent. Overall, Z-score normalization improves model stability and accuracy by ensuring consistent data representation across all features.

Z-score normalization, otherwise called standardization, converts data by focusing it on 1 with a standard deviation of 1. During this Data-Driven Demand Forecasting method, this method aids process changes in sales data, like seasonal spikes and changing demand designs. It is calculated utilizing the equation:

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

Whereas X signifies new value, μ and σ refers to mean and standard deviation. Transforming data into a normal scale enhances the performance of the model by creating features corresponding, decreasing bias, and improving predictive precision in predicting upcoming demand tendencies.

B. Demand Forecasting Model: PNVSS

Moreover, the PNVSS technique is employed for the data-driven demand prediction model [19]. This model is chosen due to its capacity to effectually handle uncertainty and imprecision in the data, which is common in real-world forecasting scenarios. Unlike conventional methods, PNVSS incorporates vagueness and conflicting information, making it highly appropriate for complex, uncertain environments. It allows the model to manage both qualitative and quantitative data, giving a more complex understanding of demand patterns. Furthermore, PNVSS can handle incomplete and ambiguous data, enhancing the robustness of the forecasting model. Compared to other techniques namely traditional soft sets or fuzzy logic, PNVSS gives superior flexibility in dealing with diverse types of uncertainty. This results in more accurate and reliable demand predictions, particularly in dynamic and rapidly changing markets.

Definition2.1: Let X is a universe. A NS A on X is described as demonstrated:

$A = \{\langle x, T_A , I_A\ F_A(x)\rangle : x \in X\}$ whereas $T, I, F : X \to [0,1]$ and $0 \leq T_A(x) + l_A(x) + F_A(x) \leq 3$.

Now, $T_A(x)$ refers to membership degree, $I_A(x)$ signifies indeterminacy degree and $F_A(x)$ stands for non-membership degree.

Definition2.2: A set of vague is identified by the true membership function (MF) t_v and a false MF f_v, whereas $t_u(x)s$ a lower limit on the membership grade of x originated from the proof of x, and $f(x)$ denotes a lower limit on the negation of x based on the proof against x. $t_v(x)$ and $f_v(x)$ both values are specified on the closed interval [0,1] with every point in a principle set X, while $t_v(x) + f_v(x) \leq 1$.

Definition2.3: A Neutrosophic vague set ANV (NVS) on X noted as:

$A = \{\langle \text{x}; \hat{T}_A(x); \hat{I}_A(x); \hat{F}_A(x)\rangle; x \in X\}$ of which indeterminacy, truth, and false membership functions are described as:

$$\hat{T}_A(x) = [T^-, T^+], \hat{I}(x)[I^-, I^+], \hat{F}_A(x) = [F^-, F^+]$$

Whereas, (1) $T^+ = 1 - F^-$ (2) $F^+ = 1 - T^-$ and (3) $0 \leq T^- + I^- + F^- \leq 2^+$ if X is constant, an NVS A might be described

$$A = \int \langle \text{x}; \hat{T}_A(x); \hat{\text{I}}_A(x); \hat{F}_A(x)\rangle/\text{x}, x \in X$$

If X is separate, an NVS A may be written

$$A = \sum_{i=1}^{n} \langle \text{x}; \hat{T}_A(x); \hat{I}_A(x); \hat{F}_A(x)\rangle/x_i, x_i \in X$$

Definition2.4: Let X is a universe. A Penta-partitioned NS A on X is identified as

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

Here, $T, C, G, U, F: X \to [0,1]$ and $0 \leq T_A(x) + C_A(x) + G_A(x) + U_A(x) + F_A(x) \leq 5$. Now $U_A(x)$, $T_A(x)$, $C_A(x)$, $G_A(x)$ and $F_A(x)$ refers to unknown, truth, contradiction, ignorance, and false memberships.

Definition2.5: A Pentapartitioned Neutrosophic Vague Set $A_{\widetilde{PNV}}$ ($\widetilde{PNV}$ is abbreviated) on the discourse universe indicated

$$A_{\widetilde{PNV}} = \{\langle x; \hat{T}_{A_{\widetilde{PNV}}}(x); \hat{C}_{A_{\widetilde{PNV}}}(x); \hat{G}_{A_{\widetilde{PNV}}}(x); \hat{U}_{A_{\widetilde{PNV}}}(x); \hat{F}_{A_{\widetilde{PNV}}}(x)\rangle \,; x \in X\}$$

$$\hat{T}_{A_{\widetilde{PNV}}}(x) = [T^-, T^+], \hat{C}_{A_{\widetilde{PNV}}}(x) = [C^-, C^+], \hat{G}_{A_{\widetilde{PNV}}}(x) = [G^-, G^+]$$

$$\hat{U}_{A_{\widetilde{PNV}}}(x) = [U^-, U^+], \hat{F}(x) = [F^-, F^+],$$

Whereas (1) $T^+ = 1 - F^-$(2)$F^+ = 1 - T^-$(3)$C^+ = 1 - U^-$(4)$U^+ = 1 - C^-$(5) $0 \leq T^- + C^- + G^- + U^- + F^- \leq 4^+$

Definition2.6: Assume that $A_{\widetilde{PNV}}$ and $B_{\widetilde{PNV}}$ be dual $\widetilde{PNV}S$ of the universe U. When $\forall x \in U$,

$\hat{T}_{A_{\widetilde{PNV}}}(x) = \hat{T}_{B_{\widetilde{PNV}}}(x)$; $\hat{C}_{A_{\widetilde{PNV}}}(x) = \hat{C}_{B_{\widetilde{PNV}}}(x)$; $\hat{G}_{A_{\widetilde{PNV}}}(x) = \hat{G}_{B_{\widetilde{PNV}}}(x)$; $\hat{U}_{A_{\widetilde{PNV}}}(x) = \hat{U}_{B_{\widetilde{PNV}}}(x)$; $\hat{F}_{A_{\widetilde{PNV}}}(x) = \hat{F}_{B_{\widetilde{PNV}}}(x)$ then the $\widetilde{PNV}S$ $A_{\widetilde{PNV}}$ and $B_{\widetilde{PNV}}$ are equivalent.

Definition2.7: The inverse of $\widetilde{PNV}S\hat{T}_{A_{\widetilde{PNV}}}$ known as$A^C_{\widetilde{PNV}}$ and is identified by $\hat{T}^C_{A_{\widetilde{PNV}}}(x) = [1 - T^+, 1 - T^-]$, $\hat{C}^C_{A_{\widetilde{PNV}}}(x) = [1 - C^+,\ 1 - C^-]$, $\hat{G}^C_{A_{\widetilde{PNV}}}(x) = [1 - G^+, 1 - G^-]$, $\hat{U}^C_{A_{\widetilde{PNV}}}(x) = [1 - U^+, 1 - U^-]$, $\hat{F}^C_{A_{\widetilde{PNV}}}(x) = [1 - F^+, 1 - F^-]$

Definition3.1: Let U be a universe, E a collection of parameters, and $A \subseteq E$. A group of pairs $(\hat{F}, A)$ is named a PNVSS over U whereas $\hat{F}$ refers to mapping provided by

$$\hat{F}: A \to PNV(U)$$

and $PNV()$ signifies the collection of each of a PNV subset of U.

Sample3.2: Assume that $U = \{r_1, r_2, r_3, r_4\}$ is a collection of universe-demonstrating residential units. Assume $A = \{a_1, a_2, a_3\} = \{$larger, smaller, medium$\}$ is a collection of parameters describing the residence size. Describe a mapping

$$\hat{F}a: A \to PNV$$

$$\hat{F}(a_1)$$

$$= \left\{\begin{matrix} \dfrac{r_1}{\langle [0.1,0.3]; [0.2,0.8]; [0.1,0.9]; [0.3,0.7]; [0.2,0.8]\rangle}, \dfrac{r_2}{\langle [0.1,0.7]; [0.2,0.5]; [0.3,0.9]; [0.4,0.6]; [0.5,0.6]\rangle} \\ \dfrac{r_3}{\langle [0.4,0.5]; [0.3,0.7]; [0.5,0.6]; [0.6,0.7]; [0.5,0.8]\rangle}, \dfrac{r_4}{\langle [0,0.3]; [0.2,0.4]; [0.1,0.7]; [0.8,0.9]; [0.4,0.9]\rangle} \end{matrix}\right\}$$

$$\hat{F}(a_2)$$

$$= \left\{\begin{matrix} \dfrac{r_1}{\langle [0.6,0.7]; [0.3,0.8]; [0.5,0.9]; [0.7,0.7]; [0.2,0.4]\rangle}, \dfrac{r_2}{\langle [0.2,0.3]; [0.3,0.5]; [0.5,0.9]; [0.8,0.9]; [0.7,0.9]\rangle} \\ \dfrac{r_3}{\langle [0.3,0.4]; [0.6,0.8]; [0.4,0.6]; [0.7,0.8]; [0.6,0.9]\rangle}, \dfrac{r_4}{\langle [0.1,0.3]; [0.5,0.9]; [0.2,0.7]; [0.2,0.9]; [0.4,0.6]\rangle} \end{matrix}\right\}$$

$$\hat{F}(a_3)$$

$$= \left\{\begin{matrix} \dfrac{r_1}{\langle [0.3,0.4]; [0.2,0.2]; [0.1,0.2]; [0.3,0.8]; [0.1,0.8]\rangle}, \dfrac{r_2}{\langle [0.2,0.8]; [0.5,0.7]; [0.4,0.5]; [0.6,0.7]; [0.5,0.9]\rangle} \\ \dfrac{r_3}{\langle [0.3,0.6]; [0,0.7]; [0.7,0.9]; [0.4,0.8]; [0.2,0.6]\rangle}, \dfrac{r_4}{\langle [0.5,0.6]; [0.3,0.8]; [0.6,0.9]; [0.4,0.7]; [0.2,0.9]\rangle} \end{matrix}\right\}$$

Definition3.3: Assume that $(\hat{F}, A)$ and $(\hat{G}, B)$ is dual (PNVSSs) through a universe U. A (PNVSS) $(\hat{F}, A)$ is a sub-set of $(\hat{G}, B)$ and known as $(\hat{F}, A) \subseteq (\hat{G}, B)$ if and only if

1.$A \subseteq B$, and 2.$\forall a \in A, \hat{F}(a)$ refers to the PNV sub-set of $\hat{G}(a)$.

Definition3.4: Let $(\hat{F}, A)$ and $(\hat{G}, B)$ are (PNVSSs) across the universe U. A (PNVSS) $(\hat{F}, A)$ is equivalent to $(\hat{G}, B)$ and designated as$(\hat{F}, A) = (\hat{G}, B)$ if everyone is a sub-set of other.

Definition3.5: Considering (PNVSS) ($\hat{F}A$) through a universe $U, (\hat{F}, A)$ is named a null (PNVSS) mentioned as ψ_{At} when $T_{\hat{F}_{(a)}}(m) = [0,0]$, $C_{\hat{F}_{(a)}}(m) = [0,0]$, $G_{\hat{F}_{(a)}}(m) = [1,1]$, $U_{\overline{F}}(m) = [1,1]$, and $F_{\hat{F}_{(a)}}(m) = [1,1]$, $\forall m \in U$ and $\forall a \in A$.

Definition3.6: Then PNVSS $(\hat{F}, A)$ across a universe $U, (\hat{F}, A)$ is named an absolute (PNVSS) so-called $\widehat{\Psi}$, when $\forall m \in U$ and $\forall a \in A$, $T_{\hat{F}_{(a)}}(m) = [1,1]$, $C_{\hat{F}_{(a)}}(m) = [1,1]$, $G_{\hat{F}_{(a)}}(m) = [0,0]$, $U_{\hat{F}_{(a)}}(m) = [0,0]$, and $F_{\hat{F}_{(a)}}(m) = [0,0]$.

C. Parameter Optimizer: COA Model

At last, to improve the prediction performance of the PNVSS technique, the parameter tuning process is performed through COA [20]. This technique is chosen due to its efficiency in exploring large solution spaces while balancing exploration and exploitation. This metaheuristic algorithm replicates the hunting behaviour of cheetahs, enabling it to quickly converge to optimal or near-optimal solutions. Compared to other optimization algorithms such as genetic algorithms (GA) or particle swarm optimization (PSO), COA is specifically effectual in complex, non-linear optimization problems due to its fast convergence rate and capability to avoid local optima. COA also needs lesser iterations to find optimal solutions, enhancing computational efficiency. Its robustness in handling diverse optimization problems, comprising multi-modal and high-dimensional tasks, makes it highly appropriate for fine-tuning model parameters in demand forecasting models. Overall, COA confirms higher accuracy, faster processing, and more reliable optimization outputs. Fig. 2 portrays the flowchart of COA.

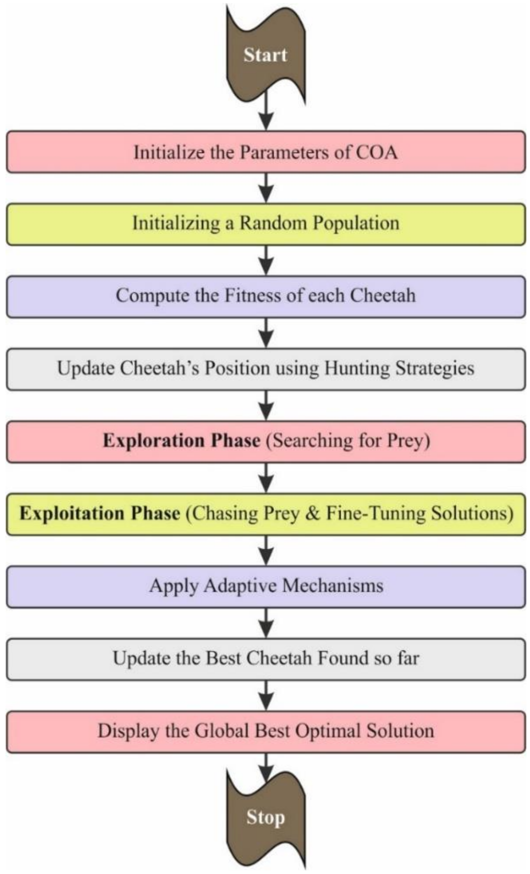

Figure 2. Flowchart of COA

COA is a significant metaheuristic model to resolve the problem in a real-time setting. It is a bio-inspired optimizer model reliant on the chasing and hunting behaviours of $cheetahs^{1,53}$. this model simulates the adaptive, faster, and effective searching approach of cheetahs, making it a promising strategy for resolving optimizer concerns comprising those found in the signalling process. It follows the main advances in the signalling process domain namely faster convergence, higher accuracy, sturdiness in noise data, effectually selecting features, and effective signalling reconstruction. The mathematical technique intended for this optimizer model is similar to searching the nature of a cheetah. It contains 4 stages such as searching, waiting for the prey, attacking prey leaving the prey, and returning home.

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Search for prey

To discover the prey's adjacent place of cheetah begins scanning and searching territory. During the period of hunting the prey, the cheetah is employed for seeking the prey in dual methods. Cheetah determines their hunting chance depending upon the coverage region of prey condition.

When the cheetah tries to hunt the prey in denser regions it is employed for implementing the sitting and searching technique, the cheetah is represented by the $X_{i,j}^{t}$ in which I signifies the existing location $(i = 1,2, \dots \dots \dots, n)$, n is cheetah counts and j $(j = 1,2, \dots \dots \dots, D)$ is the arrangement and position of the cheetah in dimension D. i upgrades the existing location of a cheetah.

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \widehat{r_{i,j}^{-1}}.a_{i,j}^{t} \tag{2}$$

Now $X_{i,j}^{t+1}$ represents the further location of the cheetah, $X_{i,j}^{t}$ is the existing location, t signifies the search period, $a_{i,j}^{t}$ denotes step length of the cheetah and $r_{i,j}^{-1}$ represents randomization parameter.

Waiting for the prey

To scan the area, cheetahs use to sit and wait for victim. And it tries to come closer near their prey by lying and hiding for catching the prey. Then, they will wait for a certain time to come near the prey.

$$X_{i,j}^{t+1} = X_{i,j}^{t} \tag{3}$$

In this approach, every cheetah in the dimensions upgraded to enhance searching achievement and also to evade convergence of premature.

Attack the prey

Every time, the cheetah observed the prey it hurried for attacking the prey at very high speed. The cheetah tries to travel in the prey's direction to fine-tune the locations and intends to block the prey way. During the search, each cheetah in the dimensions fine-tuned its location of adjacent cheetah.

$$X_{i,j}^{t+1} = X_{B,j}^{t} + \check{\check{r}}_{i,j}.\beta_{i,i}^{t} \tag{4}$$

From the equations $X_{B,j}^{t}$ is the existing location of prey, $r_{i,j}$ is the adjusting factor, and $\beta_{i,i}^{t}$ is the interaction factor of cheetahs.

In this paper, the COA is applied to define the hyperparameter included in the PNVSS method. The MSE is measured as objective function.

$$MSE = \frac{1}{T} \sum_{j=1}^{L} \sum_{i=1}^{M} \left(y_j^i - d_j^i\right)^2 \tag{5}$$

Here, M and L characterize the resulting value of data and layer respectively, d_j^i and y_j^i indicates the appropriate and attained sizes for j^{th} unit from the resulting layer of a network in tth time consistently. Algorithm 1 demonstrates the COA methodology.

Algorithm 1: COA technique

Initialize Population:
Define the population size P and initialize a set of P cheetahs. Each cheetah depicts a potential solution to the optimization problem.
Each cheetah has a position X_i and a fitness value $F(X_i)$.
Evaluate Fitness:
Evaluate the fitness of each cheetah in the population by utilizing the objective function.
The fitness function $F(X_i)$ is usually a measure of how well a solution meets the desired criteria (e.g., minimal error, maximal performance).
Update Best Position:
Identify the best cheetah (with the highest fitness value), and set its position as the global best X_{best}.
Hunting Process:
Cheetahs perform a hunting process, where each cheetah updates its position based on two components:
Exploitation: Cheetah moves toward the best-known solution.
Exploration: Cheetah explores random regions of the solution space.

The new position of cheetah i is given by:

$$X_i(t+1) = X_i(t) + \alpha \cdot \left(X_{best} - X_i(\mathrm{t}) + \beta \cdot \left(X_{rand} - X_i(\mathrm{t})\right)\right)$$

Here, α and β are scaling factors that control the movement towards the optimum solution and random exploration, respectively.

X_{rand} is an arbitrarily chosen position of the cheetah.

Update Position and Velocity:

Update the velocity of each cheetah as it moves through the search space. The velocity update is influenced by its previous velocity and the best position found so far.

Cheetah's Hunting Strategy:

Implement the hunting strategy, which comprises modifying the velocity and position of the cheetah to simulate the hunting and chasing behavior. The position update balances between the global optimum solution and random movement based on predefined hunting parameters.

Termination Criteria:

Repeat steps 2 to 6 until one of the following conditions is met:

The maximum number of iterations is attained.

The desired level of fitness is achieved.

Return the Best Solution:

Once the termination criteria are met, return the best solution X_{best}.

4. Experimental Validation

The performance validation of the BIFDDF-PNVSS methodology is examined under the demand forecasting dataset [21].

4.1. Experimental Validation Evaluation Metrics for Regression Models

The performance of the regression models is computed by utilizing diverse metrics. Eq. (6) depicts MSE, which measures the average squared difference between the predicted and actual values, giving a sense of the error's magnitude. Eq. (7) computes RMSLE, the root mean squared logarithmic error, which is specifically beneficial for dealing with datasets that have a wide range of values. Eq. (8) defines MAE, which computes the average absolute error, giving a more interpretable measure of prediction accuracy. Eq. (9) exhibits MAPE, which computes the percentage difference between predicted and actual values, presenting a relative error metric that is useful for comparing performance across diverse datasets. These metrics give a comprehensive evaluation of model performance as demonstrates by the following equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(log(1+y_i) - log(1+\hat{y}_i)\right)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{9}'$$

Where,

- y_i represents the actual values
- $\hat{y}_i$ depicts the predicted values
- n denotes the number of data points

These metrics give a comprehensive evaluation of the performance of the model, including its capability to minimize errors and handle large-scale discrepancies in the data. The inclusion of MSE, RMSLE, MAE, and MAPE presents insights into the efficiency of the model in giving accurate and reliable predictions across various regression tasks.

4.2. Results and Discussion: Performance Evaluation and Comparative Analysis

Table 1 and Fig. 3 exemplify the training set (TRAST) and testing set (TESST) analysis of the BIFDDF-PNVSS technique based on dissimilar metrics. Based on TRAST, the BIFDDF-PNVSS method gains MSE, RMSLE, MAE, and MAPE of 0.0031, 0.0559, 0.0325, and 38.181, respectively. Similarly, based on TESST, the BIFDDF-PNVSS method obtains MSE, RMSLE, MAE, and MAPE of 0.0008, 0.0273, 0.0184, and 67.9795, respectively.

Table 1: TRAST and TESST outcome of BIFDDF-PNVSS model under various metrics

Metrics	TRAST	TESST
MSE	0.0031	0.0008
RMSLE	0.0559	0.0273
MAE	0.0325	0.0184
MAPE	38.181	67.9795

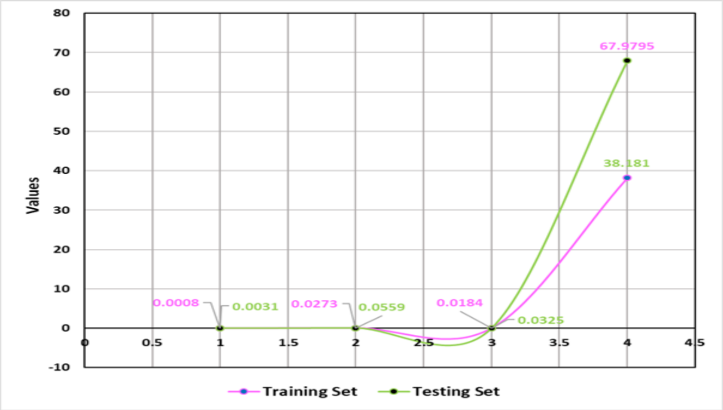

Figure 3. TRAST and TESST outcome of BIFDDF-PNVSS model under various metrics

Fig. 4 signifies the actual vs prediction result of the BIFDDF-PNVSS technique based on epochs 10-50. The figure implies that the BIFDDF-PNVSS approach suitably predicted the solution. It is similarly observed that the forecast values by the BIFDDF-PNVSS approach are closer to the actual values.

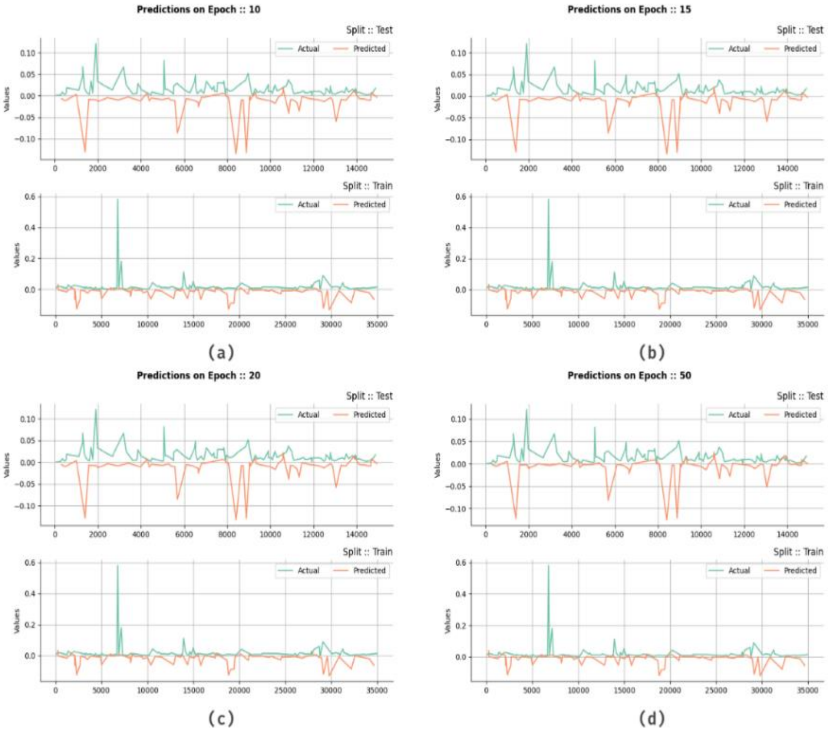

Figure 4. Actual vs Prediction outcome of BIFDDF-PNVSS technique on (a-d) Epochs 10, 15, 20 and 50

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Fig. 5 states loss curves of the BIFDDF-PNVSS technique based on multiple metrics of MAE, MAPE, MSE, and RMSLE. The values of loss are calculated across a period of 0-50 epochs. It is exemplified that the values of training prove a diminishing propensity, which indicates proficiency in equalizing an equilibrium among generalization and data fitting. The successive dilution in loss values as well as securities the higher performance and tune the prediction results gradually.

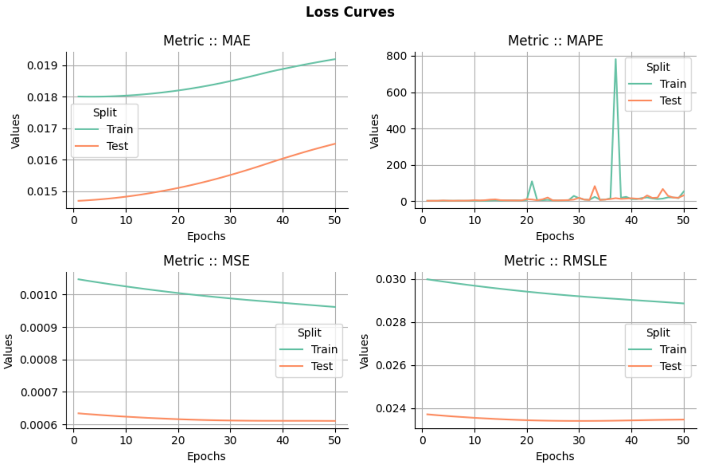

Figure 5. Loss curves of BIFDDF-PNVSS model under various metrics

4.3. Comprehensive Comparative Analysis of the Performance of the BIFDDF-PNVSS Model in Comparison with a Variety of Existing Techniques and Methodological Approaches

Table 2 highlights the comparative study of the BIFDDF-PNVSS model with existing methodologies based on distinct measures like MSE, MAE, and MAPE [22, 23]. The BIFDDF-PNVSS model illustrates the optimum performance with the lowest MSE of 0.0008, MAE of 0.0184, and MAPE of 72.4107, outperforming all other models listed. Notably, the NP-ARMA and NPAR models exhibit slightly higher errors across all metrics, followed by ESM and Ensemble (C), which exhibit progressively higher MSE, MAE, and MAPE values. The GSM, SVR, and SSA-Elman models also show higher error rates, confirming the superior accuracy of the BIFDDF-PNVSS model in forecasting. This highlights the efficiency of the BIFDDF-PNVSS technique in minimizing prediction errors when compared to the other techniques.

Table 2: Comparative analysis of BIFDDF-PNVSS model with existing techniques

Model	**MSE**	**MAE**	**MAPE**
BIFDDF-PNVSS	0.0008	0.0184	72.4107
NPAR	0.0010	0.0186	71.8707
NP-ARMA	0.0011	0.0187	71.1707
ESM	0.0013	0.0189	70.6107
Ensemble (C)	0.0014	0.0191	69.9407
GSM Method	0.0016	0.0192	69.1607
SVR	0.0017	0.0194	68.4807
SSA-Elman	0.0019	0.0196	67.9807

Fig. 6 reveals the MSE result of the BIFDDF-PNVSS approach with existing techniques. The proposed BIFDDF-PNVSS method reaches a decreased MSE of 0.0008, while the existing methodologies namely NPAR, NP-ARMA, ESM, Ensemble (C), GSM, SVR, and SSA-Elman have obtained better MSE of 0.0010, 0.0011, 0.0013, 0.0014, 0.0016, 0.0017, and 0.0019, respectively.

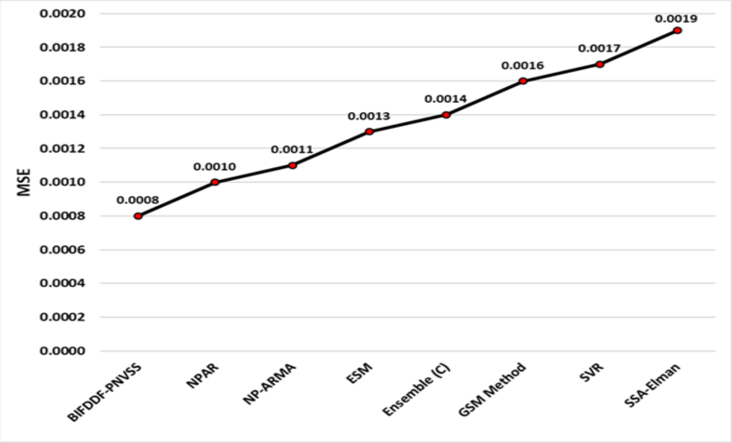

Figure 6. MSE outcome of BIFDDF-PNVSS model with existing techniques

MAE analysis of the BIFDDF-PNVSS approach with existing methods is displayed in Fig. 7. The proposed BIFDDF-PNVSS method gains a minimum MAE of 0.0184, while the existing models namely NPAR, NP-ARMA, ESM, Ensemble (C), GSM, SVR, and SSA-Elman have accomplished better MSE of 0.0186, 0.0187, 0.0189, 0.0191, 0.0192, 0.0194, and 0.0196, respectively.

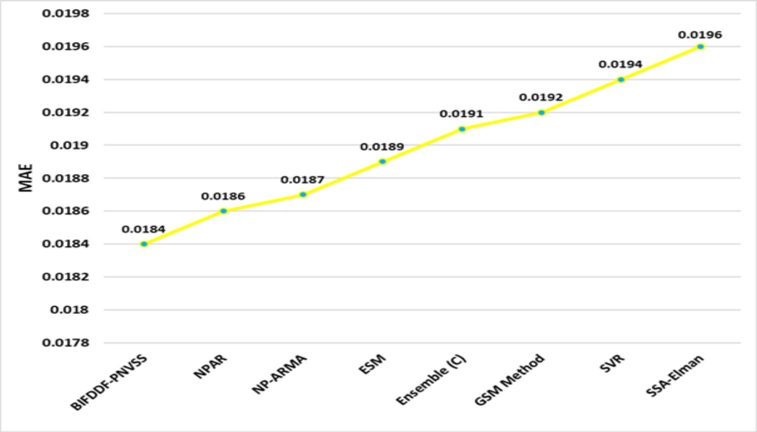

Figure 7. MAE outcome of BIFDDF-PNVSS model with existing techniques

Fig. 8 depicts the MAPE solution of BIFDDF-PNVSS technique with existing approaches. The proposed BIFDDF-PNVSS technique gains a better MAPE of 72.4107, while the existing methodologies namely NPAR, NP-ARMA, ESM, Ensemble (C), GSM, SVR, and SSA-Elman have reached lesser MAPE of 71.8707, 71.1707, 70.6107, 69.9407, 69.1607, 68.4807, and 67.9807, correspondingly.

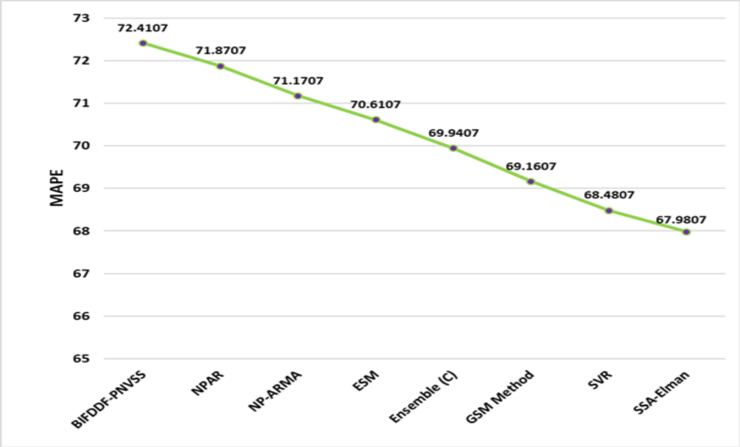

Figure 8. MAPE outcome of BIFDDF-PNVSS model with existing techniques

4.4. Comprehensive Performance Comparison of the BIFDDF-PNVSS Model Against Various Existing Techniques and Methodological Approaches

Table 3 and Fig. 9 illustrates the computational time (CT) in seconds for various models, with the BIFDDF-PNVSS model achieving the fastest CT of 3.08 seconds. This highlights the efficiency of the BIFDDF-PNVSS model, significantly outperforming other models such as NPAR with 9.46 seconds, NP-ARMA with 9.01 seconds, and ESM with 7.78 seconds, which require longer processing times. The Ensemble C model takes 7.44 seconds, while the GSM and SVR models require 7.27 and 7.62 seconds, respectively. SSA-Elman, though faster than many, still takes 6.13 seconds. These results demonstrate that the BIFDDF-PNVSS technique is not only more accurate but also computationally more effectual, making it a practical choice for real-time applications.

Table 3: CT evaluation of BIFDDF-PNVSS approach with existing methods

Approach	**CT (sec)**
BIFDDF-PNVSS	3.08
NPAR	9.46
NP-ARMA	9.01
ESM	7.78
Ensemble (C)	7.44
GSM Method	7.27
SVR	7.62
SSA-Elman	6.13

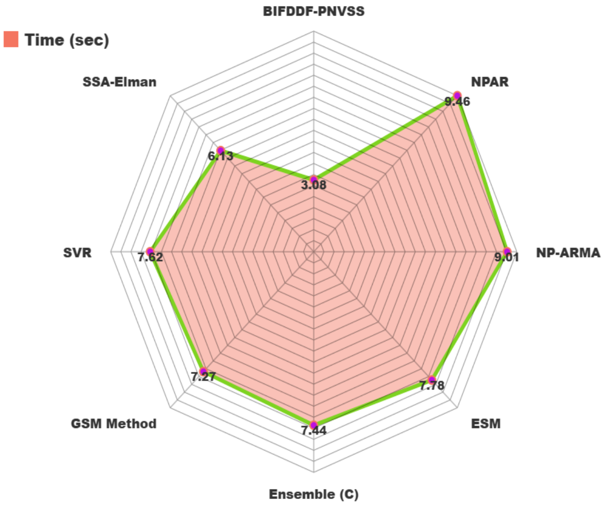

Figure 9. CT evaluation of BIFDDF-PNVSS approach with existing methods

4.5. Evaluation of Computation Time and Ablation Study: Analysing the Efficiency and Contribution of Key Components in the BIFDDF-PNVSS Model

Table 4 and Fig. 10 specifies the ablation study of the BIFDDF-PNVSS model highlighting its superior performance in comparison to PNVSS and COA models across key metrics. The BIFDDF-PNVSS model attains the lowest MSE, MAE, and MAPE values, depicting its higher accuracy and efficiency in demand forecasting. Particularly, the MSE for the BIFDDF-PNVSS model is 0.0008, MAE is 0.0184, and MAPE is 72.41, outperforming PNVSS and COA. PNVSS exhibits slightly higher MSE and MAE values at 0.0015 and 0.0189, respectively, along with a MAPE of 71.81. The COA model performs the least favourably with an MSE of 0.0020, MAE of 0.0196, and MAPE of 71.22. These outputs underscore the effectiveness of the BIFDDF-PNVSS technique in delivering more accurate demand predictions by effectively utilizing its unique combination of data pre-processing, optimization, and prediction techniques.

Table 4: In-depth analysis of the ablation study for the BIFDDF-PNVSS methodology compared to existing models

Model	MSE	MAE	MAPE
BIFDDF-PNVSS	0.0008	0.0184	72.4107
PNVSS	0.0015	0.0189	71.8107
COA	0.0020	0.0196	71.2207

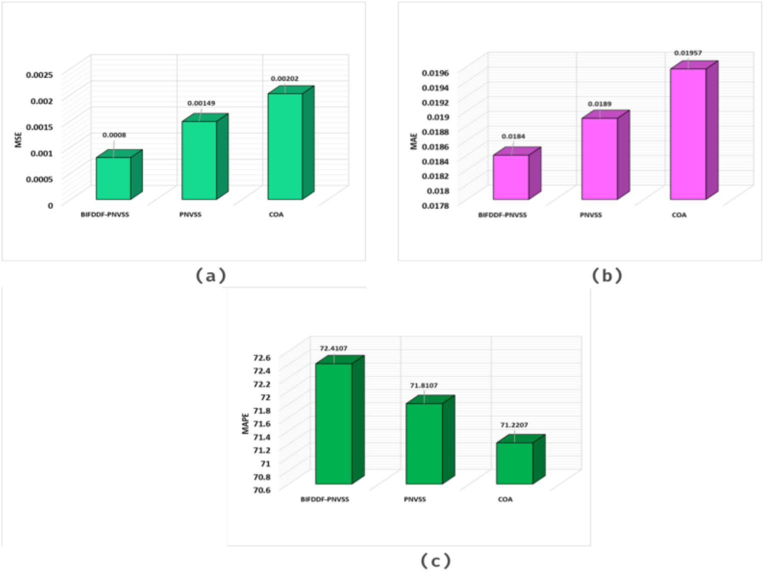

Figure 10. In-depth analysis of the ablation study for the BIFDDF-PNVSS methodology compared to existing models

5. Conclusion

In the manuscript, a novel BIFDDF-PNVSS technique is proposed. The main goal of the BIFDDF-PNVSS technique is to progress the accurate BI structure for the demand forecasting method. It contains three distinct kinds of processes like data normalization, demand forecasting model, and parameter selection. Initially, the data pre-processing stage is applied to convert input data into a beneficial format by the Z-score normalization method. Furthermore, the PNVSS technique is employed for the data-driven demand prediction model. Finally, to improve the prediction performance of the PNVSS model, the parameter tuning process is performed by implementing the COA model. A comprehensive experimentation is performed to verify the performance of the BIFDDF-PNVSS methodology under the demand forecasting dataset. The BIFDDF-PNVSS methodology outperforms existing techniques with a superior MSE of 0.0008, demonstrating its exceptional accuracy in demand forecasting compared to other models.

5.1. Evaluation of Limitations and Opportunities for Improvement: Insights into the BIFDDF-PNVSS Model and Potential Avenues for Future Research

The limitations of the BIFDDF-PNVSS methodology comprise the dependence on a single optimization approach, which may not perform equally well across all problem domains. Furthermore, the performance of the model could be influenced by the quality and availability of data, specifically in situations where data is noisy or incomplete. The study also does not account for real-time data updates, which could affect the accuracy of predictions in dynamic environments. Moreover, the computational complexity of the technique could increase with the size of the problem, potentially restricting its scalability. Future work should concentrate on improving the adaptability of the model to diverse types of data and enhancing its efficiency for large-scale applications. Additionally, incorporating hybrid optimization techniques could additionally enhance the robustness and performance of the model in intrinsic real-world scenarios.

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