Wind power forecasting under nonlinear conditions using fuzzy time series and long-short term memory models

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ABSTRACT

In the present day, there has been an increased focus on sources of clean energy, especially wind, since the depletion of fossil fuel reserves. Using the possibility of wind speed presents obstacles and complexities due to its non-linear characteristics. Therefore, a precise and effective wind energy forecast will greatly assist in resolving the system's operating and planning issues. The forecasting of wind power is done through three forecasting techniques, the fuzzy time series (FTS) method, the long-short term memory (LSTM) and auto-regressive integrated moving average (ARIMA) method of forecasting. A comparative evaluation utilizing root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) indicates that the proposed FTS approach demonstrates superior performance of RMSE of 3.053 and a MAPE of 17.892% relative to both LSTM of RMSE of 5.378 and a MAPE of 32.844% and ARIMA of RMSE of 3.901 and a MAPE of 25.105%, attaining the minimal prediction errors. The outcomes show that FTS is effective well for datasets with seasonal changes and small training sizes.

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1. INTRODUCTION

The world is gradually running out of fossil fuels to satisfy its energy needs, and as a result, the resources are being quickly depleted. The inherent variability and uncertainty of wind speed offer serious problems with integrating the grid and power system stability [1]. For better grid operations, accurate wind power forecasting is necessary, also less reliance on supplemental power sources, and effective energy management are needed. For wind power prediction artificial neural networks (ANNs) and auto-regressive integrated moving average (ARIMA) techniques are frequently used, by these models the intricate, nonlinear, and seasonal fluctuations in wind speed data are frequently not well characterized. The forecast grouping of each subseries is acquired to frame a more plane gradient and trademark series by conv-long-short term memory (LSTM) and a modified whale optimization algorithm (MWO), is prepared with the regeneration succession, which is handled for the forecast succession by the empirical model decomposition inversed [2]. Recent advancements in optimization-based wind energy forecasting have concentrated on addressing wake effects to enhance overall power output. An improved optimization algorithm presented improves the dynamics of exploration and exploitation, resulting in markedly increased energy production compared to traditional metaheuristic approaches [3].

An improved grey wolf optimizer (I-GWO), which reveals greater convergence rates and superior efficacy in optimizing wind farm output amidst nonlinear wake conditions is presented in [4]. K-Means clustering, LSTM networks, and variational mode decomposition (VMD) is used in a multi-scale wind power forecasting model. VMD extracts distinct frequency components from wind power signals, thereby improving forecast precision [5]. A unique deep learning-based model has been presented to analyze wind-time sequence data, taking into account the vulnerability and unstable wind speed nature [6]. The significance of the exact wind speed forecast is progressively reasonable for stable wind energy usage thinking about the developing segment of wind energy in the electric network [7]. Zhang *et al.* [8] employs LSTM and recurrent neural networks (RNNs) to forecast natural gas usage. The model considers seasonal fluctuations and external affecting variables. Shi *et al.* [9] introduces a fuzzy time series (FTS) model that reconciles precision and comprehensibility for wind power prediction. Wind power based on fuzzy model with ANN, random k nearest neighbors (K-NN), and support vector regression methods are incorporated to determine the efficient forecasting [10]. A method for assessment of an automatic control measurement system, which are based on gains of supervised machine learning algorithms like random forest and KNN were studied with high accuracy [11].

Accuracy was achieved through the utilization of a multi-layer perceptron (MLP) combiner. Numerical tests showed that prediction errors were much lower than with the naïve method [12]. The proposed method is a hybrid model that integrates group empirical mode decomposition (eEEMD) with LSTM networks for ultra-short-term wind power prediction. The suggested method breaks down the original wind power series into intrinsic mode functions that are then predicted using LSTM, which makes the predictions more accurate [13]. A hybrid deep learning method designed for utilizing meteorological data is created to enhance short-term wind energy forecasting [14]. Wind power prediction with deep learning from two viewpoints: formulations for wind power prediction with deep learning and the improvement of deep learning models is examined [15]. An advanced fuzzy intelligence system and a conv-LSTM hybrid model for renewable energy forecasting is developed to enhance prediction accuracy and reliability. The system integrates various fuzzification strategies with machine learning methodologies [16], [17].

Machine learning algorithms are required in long-term wind power forecasting, utilizing historical daily wind speed data and illustrating the capability of these models in order to identify intricate patterns in wind dynamics are investigated [18]. An innovative statistical methodology are presented, employing probabilistic modeling to evaluate uncertainties in wind predictions for short-term wind power forecasting [19], [20]. The researchers in [21], [22] introduces a wind power forecasting model that combines fuzzy clustering with an improved general regression neural network. Wang *et al.* [23] proposes a hybrid forecasting model that integrates bidirectional recurrent neural networks (Bi-RNNs) with deep belief networks (DBNs) for short-term load forecasting. Although LSTMs have shown encouraging outcomes in wind energy forecasting, they may not consistently be the most effective choice for datasets exhibiting pronounced seasonal variations [24].

Despite the progress in predictive modeling, there is a notable gap in comparative studies that evaluate the performance of FTS against advanced neural network models like LSTM and traditional methods like ARIMA for wind power forecasting. Existing studies have not fully addressed how FTS can bridge the gap between model accuracy and computational efficiency,especially for short-term forecasting.This study examines the relative efficacy of FTS and LSTM models for short-term wind power forecasting while accounting for the stochastic nature of wind power generation.This study uses wind power data from Gujarat (2023–24) to assess how well FTS and LSTM capture seasonal fluctuations. The study will concentrate on important forecasting features like mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), to identify the best technique for wind energy projection. To justify the effectiveness of the proposed approach, this study compares FTS with widely used baseline models, including LSTM and ARIMA serves as a statistical benchmark highlights the improved accuracy achieved by the FTS method. The study's findings will offer suggestions for choosing a suitable forecasting model to raise the reliability and efficiency of wind power generation systems.

2. FUZZY TIMES SERIES

FTS forecasting techniques are non-parametric methods that employ time series data and are based on fuzzy theory.The data collected was obtained from the National Institute of Wind Energy measured of the coast of Gulf of Khambhat data from Nov 2017-2018 which consisted of a total of 365 days or measurements. The fuzzy set [25] is graphically represented with the universe of discourse defined along the x-axis and the y-axis representing the degrees of membership exist between the [0,1] interval. The FTS forecast model was implemented by coding in Python. The triangular membership function is used to define the grid partitioning here in the FTS modelling for forecasting. The FTS forecast model was implemented using the pyFTS library As per the occasion's arrangement information utilized in this examination, the ranges are assembled as {very low, low, medium, high, and very high}. The partitions based on linguistic variables are divided into five levels.

VL: very low, L: low, M: medium, H: high, VH: very high.

These are further divided into seven sublevels each:

VL0, VL1, VL2.........VL6, L0, L1, L2, ….... L6, ... VH0, VH1, VH2......VH6.

FTS grid partitioning effectively segregates wind power (kW). This methodical technique guarantees a detailed representation of wind power data, enhancing forecasting precision as shown in Figure 1. The auto correlation function (ACF) is implemented for 365 days and iterated over for all the months to generate fuzzy rules and fuzzy logic.

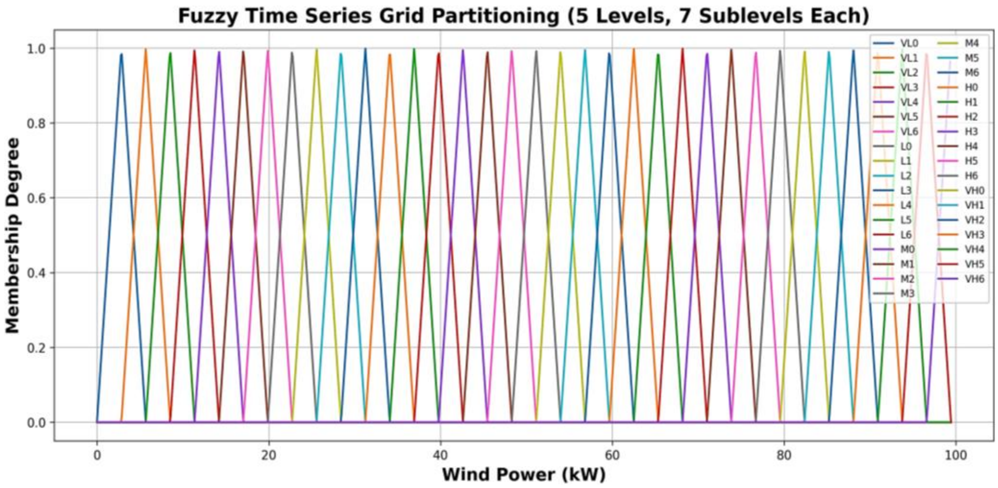

Figure 1. Grid partitioning

Depending on ACF, a set of rules are generated and implemented to build the model which further will be used to train the model and perform forecasting. Figure 2 indicates a high correlation at the start of the month and a general or gradual decline towards the end of the period and so the plot reveals strong temporal dependence and periodic behavior in the wind power data, justifying the use of nonlinear forecasting models such as FTS and LSTM.

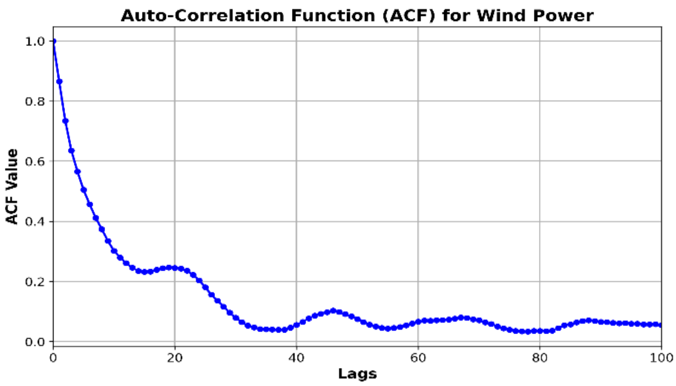

Figure 2. Auto correlation for wind power

The MSE, MAE, and MAPE metrics for 11 distinct FTS models are obtained which is shown in Table 1. A performance graph in Figure 3 depicts the ideal model based on the results. HOFTS1 exhibits the lowest RMSE (0.0497), hence demonstrating absolute precision. The MAE score of 0.0382 signifies an average prediction error and a reduced MAPE (40.99%).

Table 1. Auto correlation for wind power

Metric	RMSE	MAE	MAPE (%)
MVFTS0	0.1167	0.097	92.20
Weighted MVFTS1	0.0996	0.0787	80.81
PWFTS2	0.0934	0.0738	81.06
WHOFTS2	0.0831	0.0647	80.73
PWFTS3	0.0736	0.0571	59.94
PWFTS1	0.0694	0.0546	49.97
WHOFTS3	0.0645	0.0506	43.77
WHOFTS1	0.0615	0.0469	38.90
HOFTS3	0.0565	0.0432	35.50
HOFTS2	0.0566	0.0435	37.54
HOFTS1	0.0497	0.0382	40.99

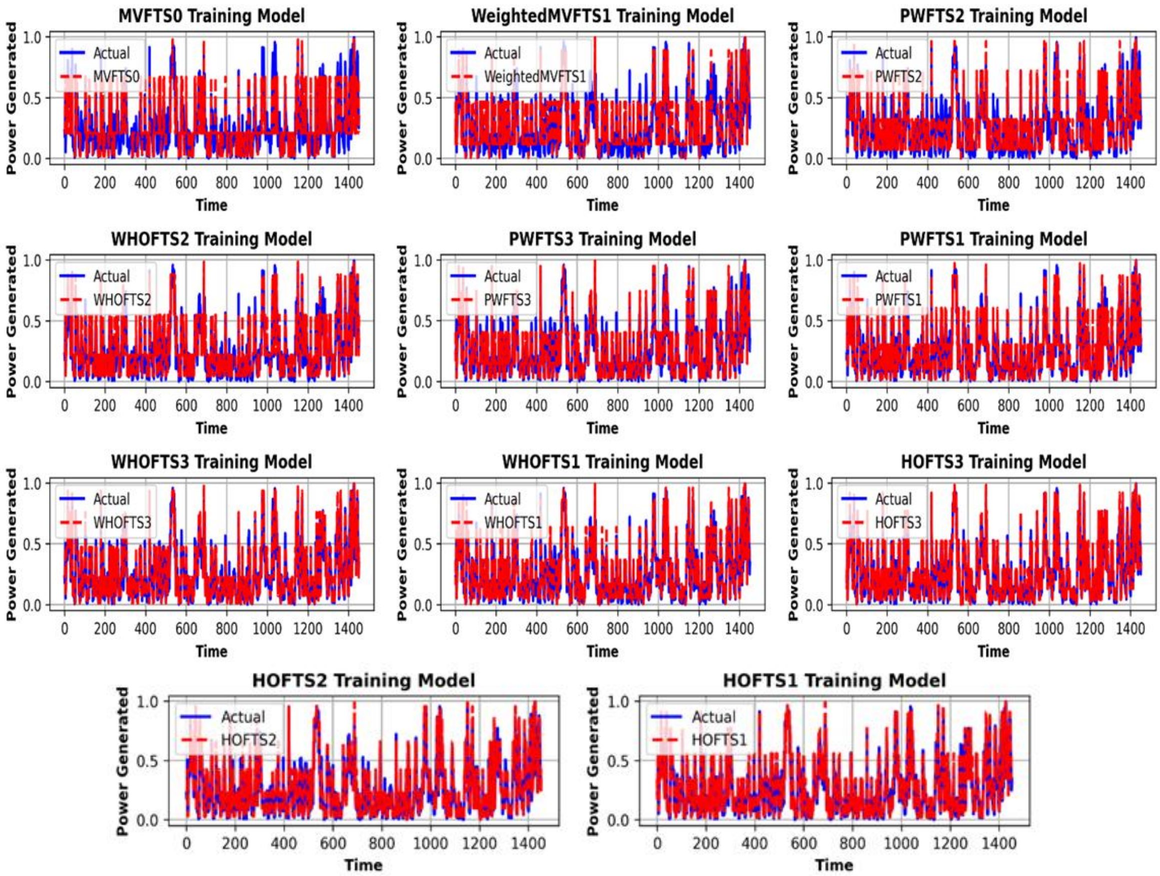

Figure 3. Training models output obtained

3. LONG SHORT-TERM MEMORY

RNNs are prepared by backpropagation through time, however learning long-haul reliance with RNNs is troublesome given slope disappearance. The use of an LSTM component is proposed to address these two problems, and over time, LSTM has emerged as the most well-known RNN structure for handling arrangement problems [26]. The short-term memory technique comes under AI-based RNNs, which utilizes memory to hold past information for a long term of time [27]. The LSTM technique can be explained in 10 stages and the block diagram explains the same as in Figure 4. The data obtained is divided into test and train data which is in one-dimensional array form. Reshaping of this array is carried out to accommodate the LSTM model and future data is predicted using the past data and inversely transformed to obtain the predicted output. performance metrics of each method is determined from (1) to (3):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \quad (2)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (3)$$

where n represents the total number of time steps (data points) used in evaluation. with hourly wind power forecasting for one year (2017-2018), n=8760 (hours in a year). for 10-minute interval data, n=52560 (10-minute intervals in a year), y_i represents the actual wind power generated at a given time step (i-th observation), $\hat{y}_i$ represents the predicted wind power at time step i using FTS and LSTM models.

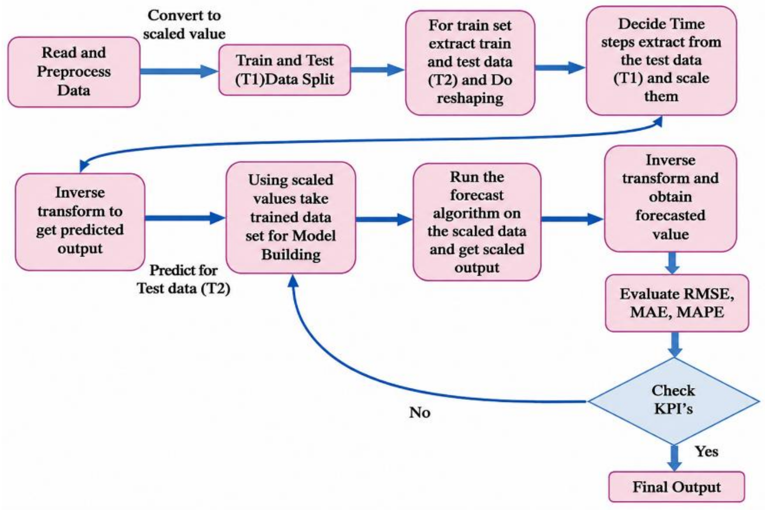

Figure 4. Flowchart for LSTM

4. RESULTS AND DISCUSSION

FTS uses fuzzy rules and discretized partitions to make step-like predictions (red lines) that work well for slow trends but might not work so well for sudden changes. FTS breaks up data into fuzzy sets and connects each range of wind speeds to set output levels. It enhances the smoothness and stability of forecasts, yet constrains their adaptability. LSTM utilizes deep learning for sequence modelling, rendering it very responsive to fluctuations. Nonetheless, issues like as overfitting and inadequate generalization lead to heightened variance in predictions, as LSTM is particularly sensitive to little variations in wind speed.

FTS model establishes a more reliable prediction trajectory with a smoother curve that aligns closely with the actual data, particularly in areas of low to moderate wind speed. The consistency arises from the linguistic granularity and rule-based framework of FTS, which excels with seasonal data or repeating patterns. In contrast, the LSTM model has a dense dispersion (green) around the real data, signifying its capacity to learn complex, nonlinear connections, including abrupt transitions which is shown in Figure 5. However, LSTM is also prone to overfitting or inaccurate predictions, particularly at low wind speeds, suggesting that its efficacy may decline in areas with less variability or useful data.

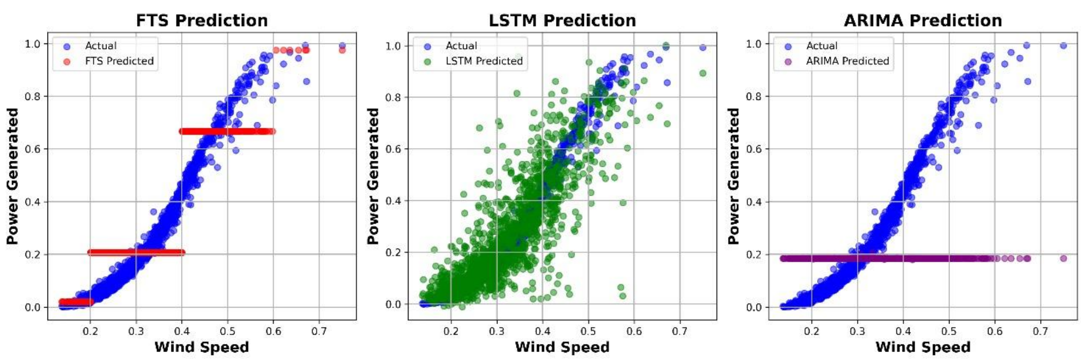

Figure 5. FTS and LSTM prediction

Table 2 presents three error measures to assess the forecasting accuracy of the models. FTS surpasses LSTM and ARIMA across all three criteria (reduced RMSE, MAE, and MAPE). FTS method exhibited superior forecasting accuracy, attaining the lowest RMSE (3.053) and MAPE (17.892%) due to its detailed representation facilitated by 100 fuzzy partitions, which enabled it to more effectively capture transition dynamics compared to the benchmark models. Conversely, the ARIMA model established with a minimal non-seasonal order (0,0,1) (0,0,1) exhibited inferior performance, yielding an RMSE of 3.901 and a MAPE of 25.105%. This outcome underscores its inadequacy in capturing the significant seasonal patterns present in hourly power-generation data, suggesting the necessity for a seasonal extension like SARIMA. The LSTM AutoReg model exhibited the highest errors (RMSE 5.378 and MAPE 32.844%), mostly due to its training being deliberately restricted to five epochs, which hindered sufficient convergence and inhibited its ability to assimilate the underlying temporal patterns. Figure 6 represents one year forecasting comparison through FTS, LSTM, and ARIMA model.

Table 2. Performance analysis

Metric	RMSE	MAE	MAPE
FTS	3.053	2.438	17.892
LSTM	5.378	4.606	32.844
ARIMA	3.901	3.327	25.105

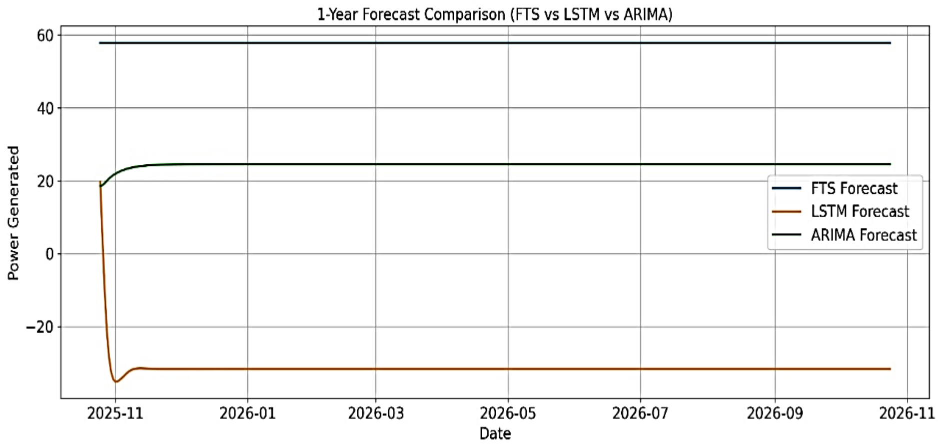

Figure 6. Forecasting – period Oct 2025- Oct 2026

Figure 7 shows FTS, LSTM, and ARIMA models performance in forecasting wind power generation using standard evaluation metrics. RMSE, MAE, and MAPE obtained from FTS is significantly lower than LSTM and ARIMA, making it relatively more reliable. The graph visually confirms that FTS consistently outperforms LSTM and ARIMA across all three metrics.

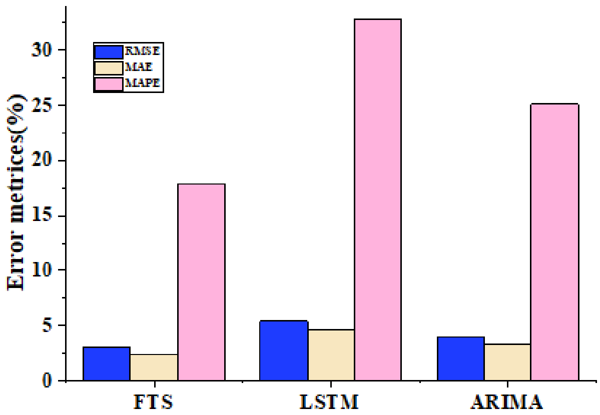

Figure 7. Comparison-FTS and LSTM performance

5. CONCLUSION

Wind power prediction utilizing historical data from October 2017 to October 2018 is assessedusing FTS and LSTM models. FTS model exhibited the lowest overall error, with an RMSE of 3.053, an MAE of 2.438, and a MAPE of 17.892%, indicating a more reliable forecasting capability compared to the other approaches. The LSTM model showed notably higher deviations, reflected in its RMSE of 5.378, MAE of 4.606, and MAPE of 32.844%. The ARIMA model delivered moderate performance, producing an RMSE of 3.901, an MAE of 3.327, and a MAPE of 25.105%, placing it between FTS and LSTM in terms of forecasting accuracy. Among the three models, FTS achieved the lowest RMSE, MAE, and MAPE, demonstrating superior capability in handling nonlinear wind-power variations. LSTM performed moderately well but showed larger dispersion, while ARIMA exhibited the highest error due to its inability to capture dynamic fluctuations. Forecasting trends for 2018-19 for FTS model yielded a consistent forecast but had difficulties in accurately reflecting abrupt fluctuations in wind power generation. The LSTM model generated a more dynamic prediction; nevertheless, its accuracy suffered due to overfitting and generalization challenges. The results show that FTS is good at predicting long-term power, while LSTM needs improvements in how it chooses features, prepares data, and optimizes hyperparameters. A hybrid approach employing FTS for long-term stability and LSTM for short-term fluctuation could enhance the accuracy of forecasting.

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AUTHOR CONTRIBUTIONS STATEMENT

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Anuradha Chandrasekar	✓	✓			✓	✓		✓	✓	✓		✓		
Padmajothi Varadarajan	✓	✓			✓	✓	✓		✓	✓				
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Devaraj Vedhagiri	✓	✓			✓	✓	✓		✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors have no conflict of interest.

DATA AVAILABILITY

The datasets supporting this work are available from the corresponding author upon reasonable request.

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