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Novel Topology for Wind Speed Forecasting based on Artificial Neural Network at Jaipur

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Abstract— **Wind power generation is increasing very rapidly all around the world. The available wind energy depends on the wind speed, which is a random variable and depends on the location and weather conditions. For the wind-farm operator, this uncertainty creates a difficulty in the system scheduling and energy dispatching, due to not knowing the wind-power generation in advance. This paper presents an artificial neural network approach for wind speed forecasting at Jaipur, India. The Back propagation (BP) learning of neural network is used for training. The accuracy of the wind speed forecasting attained with the proposed approach is evaluated by reporting the numerical results from a real-world case study. The proposed approach for wind speed forecast has the accuracy of 95% and above.**

***Keywords*— Artificial neural network, Back propagation, Wind speed, Forecasting.**

I. INTRODUCTION

Due to the limited existing reserves of fossil fuels and the harmful emissions associated with them, the demand has led to an increased focus on renewable energy sources in recent years. In the area of renewable energy, cost of solar power is too high, while, the capacity of biomass energy, tidal energy and geothermal energy are very limited. Compared with other renewable energies, wind power is more pleasurable.

Among renewable energy sources, wind energy is considered as one of the most valuable and easy-used renewable energy types [1], but is feasible only as long as weather conditions allow. To maintain economical power dispatch of wind-generated electricity, it is important to be able to make predictions of future wind speed, which directly affects generation capacity [2]. Based an accurate prediction of wind speed, the wind generating plan of a wind farm can be efficiently accommodated the impact from instable wind power on power grids [3].

Several researches [4~7] have shown that wind energy will cause the significant impacts on reserves if the technique of wind power forecasting can be improved [8]. A number of research papers [9~15] have assessed the financial benefits of good wind speed forecasting and have proven that advance forecasting techniques are required.

Artificial intelligence (AI) is a term that in broad meaning indicates the ability of a machine or artifact to perform the same kind of functions that characterize human thought. The term AI has also been applied to computer systems and programs capable of performing tasks more complex than straightforward programming [6, 7], although still far from the realm of actual thought. According to Barr and Feigenbaum, AI is the part of computer science, which is the design of intelligent computer systems, i.e. systems that exhibit the characteristics associated with intelligence in human behavior—understanding, language, learning, reasoning, solving problems and so on [8]. Several intelligent computing technologies are becoming useful as alternate approaches to conventional techniques or as components of integrated systems [9].

It is not proper to use linear methods as time series, Kalman filters, etc., because the variation of wind speed is a non-stationary and nonlinear [10]. ANN's Black Box feature is just suitable for prediction [11]. ANN can induce laws automatically and summarize input-output projection models by means of training with a great deal of input and output samples, without needing any experiential formulas [12].

This paper use Back Propagation Neural Network for prediction of wind speed with measured wind speed data from the wind data available with weather station at Jaipur. The prediction result and error of improved BPNN are presented and analyzed.

II. BRIEF INTRODUCTION OF WIND

The wind, is actually the flow of air, in terms of meteorology, it is called as airflow. Wind is produced by the difference of air pressure, which can be determined by temperature, landform, and content of atoms at the different spot. When air pressure on the surface of ground for one place is higher than another, the difference of air pressure is produced, which will generate a force which would push the air from one place with higher air pressure into the other, the movement of air is known as wind[19]. In addition, wind is influenced not only by force due to a difference of air pressure, but also by self-rotation force as well as friction force, which exists in the zone from the surface of ground into space below 1kM [20]. Wind speed is always depended on resistance as of blocking of hill, Forest, house etc. Some variation rules of wind speed have been researched by various researchers [12~21].

A. Daily variation of wind

Temperature in the daytime is higher than in the nighttime. Due to this, in the layer close to the surface of ground, wind speed is maximal after noon and gradually decreases, reaches the minimum at next sunrise. Frequency of variation in the daytime is greater than in the nighttime, especially in a clear day during summer season. However, variation rule of wind speed at the zone above the surface of ground is opposite to this i.e. maximum at sunrise and minimum at afternoon.

B. Annually variation of wind speed

In winter, the temperature of air is very low (cool), and the force produced by cool air is greater. In summer, air is very hot and humid; the force is relatively weaker. Generally, the day on which the wind speed is maximal occurs in spring, and the day on which wind speed is minimal occurs in summer.

C. Wind speed varied with altitude

Wind speed also increases with the altitude, because the friction force decreases with altitude in the so-called friction layer. Due to this, wind speed in the bottom is lower and is greater in the upper.

III. NEED FOR WIND SPEED FORECASTING

Forecasting is a vital part of business planning in today's competitive environment. However, while there is significant interest in researchers regarding prediction for wind speed, till the date, there is no reliable system for the wind speed time-series prediction.

Wind speed is a time series that can be defined as a set of observations of a single parameter, or set of different parameters, taken at a number of time intervals. These intervals are generally (although not always) of a regular length. If the time step for available data point is not consistent, or there are any data missing for some duration, this should be corrected to a regular time step if the data are required for use in forecasting. Real-world time series are diverse. Wind speed prediction is complex due to the wind's high degree of volatility and deviation[5], [8].

The wind power generated through wind energy conversion system mainly depends on the wind speed at that time. Wind speed prediction systems provide the direct information that how much wind power can be expected from wind turbine at any point of time in the next few days. Nowadays, Wind-generated power constitutes a noticeable percentage of the total electrical power demand at any instant and in some remote areas wind generated power exceeds the base load on the network. This reflects that wind is becoming a major source in electricity supply and in balancing consumer demand with power production. Wind speed and wind power forecasting is one of the most critical aspects in wind power integration with other sources and operation. It is needed to estimate the long, medium, and short-term wind speed and wind power production. The long-term wind speed forecasting is required during the planning stage of the power system, while the medium and short-term wind speed forecasting are needed in the generation unit commitment and market operation. Long-term wind power forecasting is based on long term wind patterns, while medium and short-term forecasts are generally for a few days (depends on the market operation, generally between one to three days), and hours to a few minutes, respectively [4], [12].

A major barrier to the integration of wind power into the power system grid is wind speed variability with time. Because of wind speed dependence on the weather, the output of the wind system cannot be guaranteed at any particular time. Due to this variability, the overall balance of the grid with the wind system is difficult and biases the utilization of wind power. Accurate forecasting of wind speed for power inputs from wind farms into the grid could improve the image of wind power by reducing network operation issues caused by fluctuation in the wind power. In addition, wind power, i.e. electric power generated from wind kinetic energy possesses unique characteristics and attributes that differentiate it from fossil-based electric power. Unlike fossil-fuel based power, where the rate of energy output is completely controllable, wind power is intermittent, variable, and non-dispatchable [7], [13-15]. Indeed, wind generation could vary according to weather conditions of the location. Without an energy storage system, wind energy being converted into electric power has to be consumed immediately. As a result, the economic cost of wind power generation is directly dependent on the relative synchronized between the wind speed and load patterns.

During the on-peak period of the day, the production of wind generation should command a high value of generation. While during off-peak periods, wind generation may provide very little generation or could even be removed when there is no load to serve. Furthermore, wind power generation cannot be used in the traditional generation scheduling process where controllable generators are scheduled to meet a variable load. In the generation scheduling process with wind power, it is important to incorporate the variability and intermittency characteristics. Therefore, certain power system resources must be present in the system separately to hedge against unavailability and variability of wind power during a low or no wind condition. Due to the additional reserves, the overall generation cost of the power system increases [2], [17]. Due to the adverse variability, intermittency, and controllability characteristics, wind power integration with the traditional generating system presents unique challenges. The main challenges can be grouped as challenges in forecasting wind power and challenges in management of ancillary services (regulation and reserves).

IV. ARTIFICIAL NEURAL NETWORKS

A neural network is a general mathematical computing paradigm that models the operations of biological neural systems. In 1943, McCulloch, a neurobiologist, and Pitts, a statistician, published a seminal paper titled ''A logical calculus of ideas imminent in nervous activity'' in Bulletin of Mathematical Biophysics and later in Hebb's famous organization of Behavior. The early work in AI was separated between those who believed that intelligent systems could best be built on computers modeled after brains, and those like Minsky and Papert, who believed that intelligence was fundamentally a symbol processing of the kind readily modeled on the Von Neumann computer. For a variety of reasons, the symbol-processing approach became the dominant theme in AI in the 1970s. However, the 1980s showed a rebirth in interest in neural computing.

The forward neural network is a layered network consisting of an input layer, an output layer and at least one layer of nonlinear processing elements. A typical four layered feedforward ANN is given in Fig. 1. It consists of input layer, output layer and two hidden layers. After the input and output are formulated, the next step is to incorporate the hidden layers. Number of hidden layers and number of neurons in the hidden layer are chosen by trial and error, keeping in mind that the smaller the numbers are, the better it is in terms of both memory and time requirement to implement the ANN in the motor control.

Representation of a H- layer ANN can be descried by the following two equations

$$u_i(h+1) = \sum_j w_{ij}(h+1)Y_j(h) + \theta_i(h+1) \qquad \ldots(1)$$

$$Y_i(h+1) = f[u_i(h+1)] \qquad \ldots(2)$$

where

$w_{ij}(h+1)$ Weight between ith neuron of the layer h+1 and jth neuron of layer h

$\theta_i(h+1)$ threshold to ith neuron in h+1 layer

$u_i(h+1)$ input to the ith neuron in h+1 layer

$Y_j(h)$ activation of ith neuron in hth layer

$f[.]$ Hyperbolic tangent sigmoid activation function 2/(1+exp(-2*n))-1

Nh number of neurons in the hth layer

The variable i, j and h have the following limits

$1 \le i \le N_{h+1}$, $1 \le j \le N_h$ and $0 \le h \le H-1$.

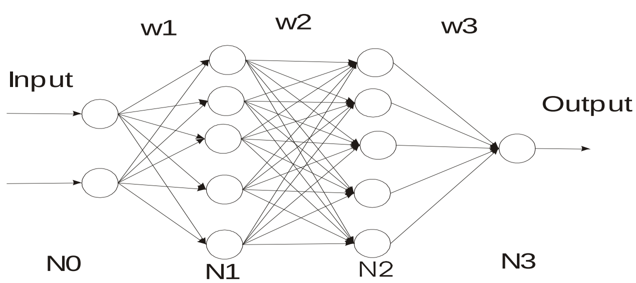


Fig. 1 Example of ANN structure

V. BACK-PROPAGATION LEARNING

A back-propagations neural network is a layered system with inputs and outputs and is composed of many simple and similar processing elements. The processing elements each have a number of internal parameters called weights. Changing the weights of an element will alter the behavior of the element and, therefore, will also alter the behavior of the whole network. The goal here is to choose the weights of the network to achieve a desired input/output relationship. This process is known as training the network.

An ANN is trained to emulate a function by presenting it with a representative set of input/output function patterns. The back-propagation training technique adjusts the weights in all connecting links and thresholds in the nodes so that the difference between actual output and the target output are minimized for all given training patterns. For the pth pattern (p=1,…P) this is done by minimizing the energy function

$$E_p = \left(\frac{1}{2}\right)\sum_i \{T_i - Y_i(H)\}^2 \qquad \ldots(3)$$

with respect to all the weights and thresholds. Y_i is activation signal and T_i is desired target. The corresponding update for the weights are calculated using the iterative gradient decent technique, where

$$\omega_{ij}^{new}(h) = \omega_{ij}^{old}(h) + \eta\,\partial E_p / \partial\,\omega_{ij}(h) + \upsilon\,\Delta\omega_{ij}(h) \qquad \ldots(4)$$

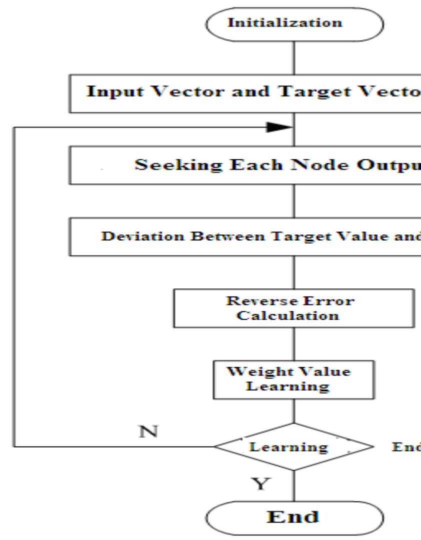


Fig. 2 Flowchart for ANN Training

The quantity $\partial E_p / \partial\,\omega_{ij}(h)$ is calculated as

$$\frac{\partial E_p}{\partial\,\omega_{ij}(h)} = \delta_i(h) + f'[u_i(h)]Y_j(h-1) \qquad 1 \le i \le N_{h+1} \qquad \ldots(5)$$

$$\delta_i(h) = \sum_j \delta_j(h+1) f'[u_j(h+1)]\,w_{ji}(h+1) \qquad \ldots(6)$$

where $\delta_i(H) = -(T_i - Y_i(H))$

The constant η is the learning step and υ is the momentum gain. $\Delta\omega_{ij}(h)$ is the change in weights in pervious iteration. Weights are iteratively updated for all training patterns. Sufficient learning is achieved when the total error function

$$E_{totali} = \sum_p E_p \qquad p = 1,\ldots\ldots\ldots, P \qquad \ldots(7)$$

summed over a set of all P training patterns goes below a preselected threshold value.

VI. BPNN FOR WIND SPEED PREDICTION

To predict a wind speed time series, the inputs of BPNN are the past sampled, lagged observations of the time series, and the output is the future values of wind speed. Generally speaking, the inputs of BPNN are composed of any moving fixed length window within the time series.

The measured wind speed data from 5 years from 1 January, 2004 to 31 December, 2009 were used as original data to train the network. The wind data of one year from 1 January, 2010 to 31 October, 2010 is used to validate the trained network. By training the network a circulate method was used, that is, we use the wind speed data of first week as an input vector, the data from next as the target vector, by each training the data set was shifted to next three hours. The data is taken for every three hours, which means in one day, there are eight data, i.e. at 00:00, 03:00, 06:00, 09:00, 12:00, 15:00, 18:00, 21:00. The weather season input is selected based on the month, as follows.

Season	Duration
Winter	1 December to 28 Feb
Spring	1 March to 31 May
Summer	1 June to 31 August
Fall	1 September to 30 November

The BPNN for wind speed prediction is

1) Identify the number of input layer and output layer nodes: The neural network is so built up that the latest 24-hour wind speed data are used as input to predict the next wind speed. The network has input layer, hidden layers and output layer. The Input nodes number of networks is 57, equaled to the data number of 24 hours and one input for the season. The output node is one for the predicted wind speed is the only one output of neural network. The logarithm function LOGSIG is chosen for the output neurons transfer function.

2) Identify the number of hidden layer and nodes: The neural network model has 57 inputs nodes and one output node. Due to complex and nonlinear nature of wind speed data, the BPNN has 2 hidden layers. After trying many configurations of hidden layers nodes, the best result is obtained for 32 and 12 nodes. The TANSIG is identified as hidden layer activation function. The BP neural network is constructed as "57-32-12-1."

3) Network training: TRAINGD is chosen as a training function, the largest number of iterative is set for 1000, and the training goal is 0.001. MATLAB toolbox of neural network is used to program to realize neural network structured learning and training process. The training phase has the following steps.

Step 1: Initialize the weights using random number

Step 2: Propagate the inputs forward

Step 3: Back propagate the error using (7) and (8)

Step 4: Terminating condition

4) Wind Speed prediction: The wind speed reference value can be predicted by trained neural network model. The corresponding wind speed value can be identified as long as input the immediate wind speed. We can see from Fig. 3-6 that predicted wind speed is consistent with the actual wind speed basically.

VII. FORECASTING ACCURACY EVALUATION

To evaluate the accuracy of the BPANN in forecasting wind speed, different criterions are used. This accuracy is computed in function of the actual wind speed that occurred. The mean absolute percentage error (MAPE) criterion, the sum squared error (SSE) criterion, and the standard deviation of error (SDE) criterion, are defined as follows.

The MAPE criterion is given by:

$$MAPE = \left(\frac{100}{N}\right)\sum_{h=1}^{N}\frac{\left|P_h - P_h\right|}{\overline{P}} \qquad \ldots(8)$$

$$\overline{P} = \left(\frac{1}{N}\right)\sum_{h=1}^{N}P_h \qquad \ldots(9)$$

where P_h and P_h are the forecasted and actual wind speed at hour h, $\overline{P}$ is the average wind power and N is the number of forecasted data.

The SSE criterion is given by:

$$SSE = 100\sum_{h=1}^{N}\left(P_h - P_h\right)^2 \qquad \ldots(10)$$

The SSE criterion is given by:

$$SDE = 100\sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(e_h - \bar{e}\right)^2} \qquad \ldots(11)$$

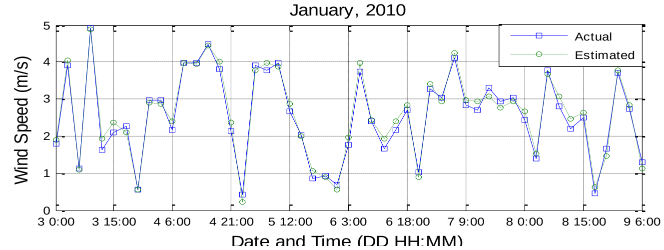
$$e_h = P_h - P_h \qquad \ldots(12)$$

$$\bar{e} = \left(\frac{1}{N}\right)\sum_{h=1}^{N}e_h \qquad \ldots(13)$$

where e_h is the forecast error at hour h, $\bar{e}$ is the average error.

VIII. CASE STUDY

The proposed BPNN approach has been applied for wind speed forecasting in Jaipur, Rajasthan, India. Wind speed forecasting is computed using only historical data. The training data is selected for 5 years from 1 January, 2004 to 31 December, 2009 corresponding to the four seasons of the year. The results have almost same accuracy distribution throughout the year that reflects reality. Numerical results with the proposed ANN approach are shown in Figs. 3–6 respectively for the winter, spring, summer and fall days. Each figure shows the actual wind power, solid line with square, together with the forecasted wind power, dashed line with circles.



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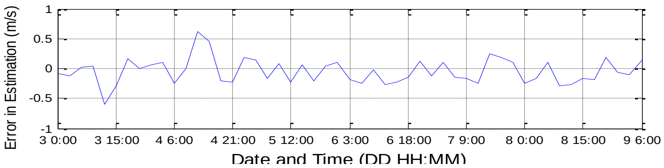

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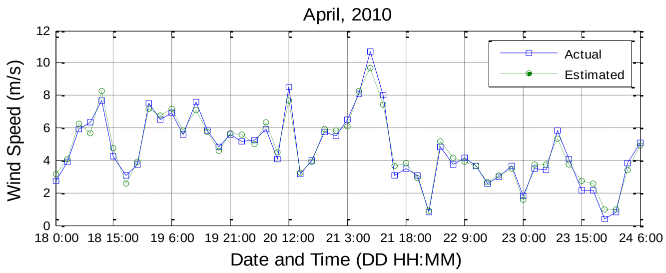
Fig. 3 Winter Season, 3 January, 2010 to 9 January, 2010: a) Actual wind speed, solid line, together with the forecasted wind speed, dashed line, in m/s b) Error in estimation, in m/s



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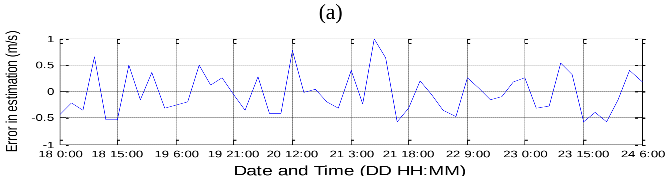
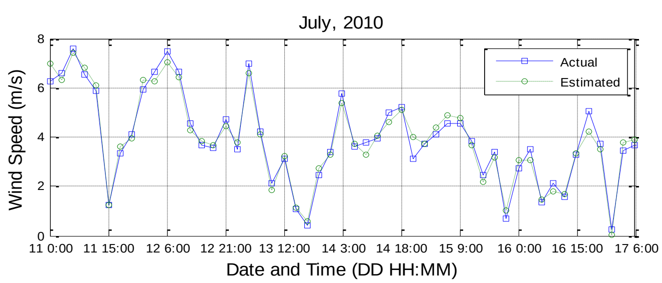


(b)

Fig. 4 Spring Season, 18 April, 2010 to 24 April, 2010: a) actual wind speed, solid line, together with the forecasted wind speed, dashed line, in m/s b) Error in estimation, in m/s



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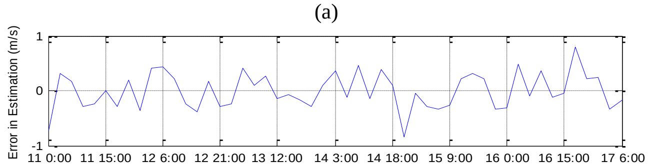
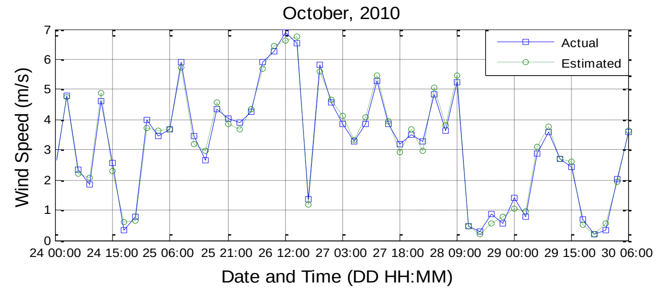


(b)

Fig. 5 Summer Season, 11 July, 2010 to 17 July, 2010: a) actual wind speed, solid line, together with the forecasted wind speed, dashed line, in m/s b) Error in estimation, in m/s



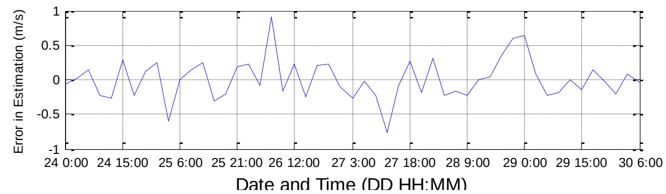


Fig. 6 Fall Season, 24 October, 2010 to 30 October, 2010: a) actual wind speed, solid line, together with the forecasted wind speed, dashed line, in m/s b) Error in estimation, in m/s

Table I presents the values for the criterions to evaluate the accuracy of the proposed ANN approach in forecasting wind speed. The first column indicates the season, the second column presents the MAPE, the third column presents the square root of the SSE, and the fourth column presents the SDE. The forecasting accuracy parameters are compared with the ANN model presented by J. P. S. Catalao et. al. [7].

TABLE I. STATISTICAL ANALYSIS OF THE DAILY FORECASTING ERROR

	MAPE		√SSE		SDE	
	x	y	x	y	x	y
Winter	9.5	4.9	593.7	123.4	34.7	7.99
Spring	9.9	6.0	578.1	285.1	42.4	19.76
Summer	6.3	4.2	232.5	170.1	17.1	22.67
Fall	3.2	5.0	207.1	139.2	14.8	18.5

x= ANN by J. P. S. Catalão et. al.[7] y= Proposed BPNN

The proposed BPNN approach presents enhanced forecasting accuracy. The MAPE has an average value of 5.08%. For comparison purposes, the average MAPE values for ARIMA and NN approaches would be 10.34% and 7.26%, respectively. Moreover, the average computation time for forecasting the wind speed for a complete week is less than 5 seconds, when used with MATLAB 7.7.0 on a PC with 2 GB of RAM and a 2.1-GHz-based processor. Hence, the proposed BPNN approach is both novel and effective for wind speed prediction.

IX. CONCLUSION

In this paper, a new Back propagation Neural Network strategy is proposed for wind speed forecasting, which takes into account the interactions of wind speed and season. The proposed strategy is composed of an efficient feature selection technique based on modified relief and mutual information techniques, and a new iterative neural network based forecasting engine. Real data Jaipur weather stations are used to test the proposed forecasting strategy. Based on the presented simulation results, the proposed forecasting framework outperforms other tested alternatives and demonstrates significant improvement compared to some of the relevant literature. A BPNN approach is proposed for wind speed forecasting in Jaipur. The application of the proposed approach to wind speed forecasting has been proven to be successful. The MAPE has an average value of 5.08%, while the average computation time is less than 5 seconds. Hence, the proposed approach presents a good trade-off between forecasting accuracy and computation time, outperforming the persistence approach.

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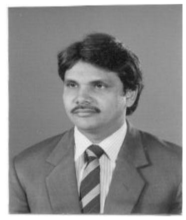

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