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ORIGINAL RESEARCH

Ensemble approach for short term load forecasting in wind energy system using hybrid algorithm

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Abstract

The uncertainty problem in the resources is essential to mitigate and to improve the system operation in order to attain the load forecasting. Sometimes, the wind power saturation level is high on the grid side; therefore wind power prediction is essential to improve the efficiency, safety, economic and stable operation of the electrical grids. In the wind energy system, balancing supply and load demands is being considered as a challenging task and it can be compensated by means of wind power forecasting. This paper depicts an ensemble approach for short term load forecasting (STLF) by means of the hybrid algorithm in the wind energy system. The hybrid algorithm is a grouping of the Deep Neural Network (DNN) and Chicken Swarm Optimization (CSO). Initially, 24 h load data of the wind energy system is collected from the New England ISO for training the DNN network thereby analyzing the load forecasting. During the training period, the training error rate is minimized with the help of the CSO algorithm. After the training period, there arises a testing period that recognizes future loads by means of the proposed hybrid algorithm. Based on the above consideration, the load forecasting problem in the wind energy system is achieved. The efficacy of the proposed method is expressed by computing the statistical measures in terms of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), respectively. The proposed method will be implemented in the Matlab/Simulink and its performances were compared with the existing methods such as DNN and ANN, respectively.

Keywords STLF · Load forecasting · Hybrid algorithm · MAPE · RMSE · Artificial Neural Network (ANN)

1 Introduction

Wind energy was considered one of the most common sources of renewable energy systems. The power obtained from the wind turbines fluctuates commonly since the wind energy fluctuates highly based on the speed and direction of the wind (Chitsazan et al. 2019). Wind energy is considered as a promising energy source, it contains environmental, social and economic benefits (Moreno and dos Santos 2018; Rejeesh 2019). Numerous nations over the world use wind energy as a sustainable power source asset. The combination of large scale wind power will convey an extraordinary shrouded threat to the sheltered and stable operation of the power framework. Because of the discontinuous generation of wind energy, it is hard to estimate the forecasting of wind power precisely. These gauges are profoundly subject to climate forecasts (Fang et al. 2019). Load forecasting provides information about the planning and implementation of an electrical system (Ribeiro et al. 2019; Shweta Sengar and Xiaodong Liu 2020). It is clear that the forecasting of any information depends on the figure of different parameters that would prompt further inaccuracy, despite the connection between the sources of input and output that perhaps predetermined during several regression strategies (Wang et al. 2019a, b, c; Ke et al. 2019; Deepa and Baranilingesan 2017; Ganguly et al. 2019; Klein et al. 2018).

Load forecasting in energy markets is a reason for market choices. There creates major challenges, strategies, critical issues and new capabilities for the mitigation of wind data uncertainties (Zhao et al. 2019). Along these lines, the accomplishment of electrical load estimation is being considered as an imperative factor for decision-makers (Li et al. 2019a, b, c; Chapaloglou et al. 2019). The forecasting

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regarding wind energy helps in enhancing the economy and safety of wind energy conversion and integration (Duan and Liu 2019). The load forecasting was classified into three categories namely: (1) Short-term load forecasting (1 h to multi-week), (2) Long-term load forecasting (longer than a year) and (3) Medium-term load forecasting (week to a year). The prediction procedures can neither be founded on the model of physical nor statistical; in addition, the model amalgamation can be a mix of different physical and statistical models that are additionally prominent (Li et al. 2019a, b, c; Yazici et al. 2019). Forecasting of wind control utilizing physical techniques relies upon Numerical-Weather-Predictions such as weight, obstacles, temperature, the harshness surface, and so forth. So in order to tackle the issues, it is important to effectively improve the controllability and predictability of wind control. Precise wind power forecasting provides an essential premise regarding power dispatching and improves the user productivity of wind energy resources (Yang et al. 2019). Also, several metaheuristic algorithms such as Falcon optimization algorithm (de Vasconcelos Segundo et al. 2019a, b), a sailfish optimizer (Shadravan et al. 2019), Meerkats algorithm (Klein et al. 2018), a metaheuristic algorithm regarding farmland fertility (Shayanfar and Gharehchopogh 2018), Owls behaviour algorithm (de Vasconcelos Segundo et al. 2019a, b), Interactive search algorithm (Mortazavi et al. 2018), Coyote optimization algorithm (Pierezan and Dos Santos Coelho 2018) and Cheetah based optimization algorithm (Klein et al. 2018) are utilized to solve constrained engineering optimization problems.

Several up to date intellectual forecasting optimization algorithms such as Fuzzy logic (Yadav et al. 2019), Artificial Neural Network and Support Vector Machines (Tian et al. 2019) were practised generally in short term load forecasting of the wind energy system. Also, it helps in resolving the load forecasting problem of time series by means of a non-linear pattern. But the ANN network finds difficulties in predicting the time interval was considered as a major drawback. When compared with the ANN, the DNN has more advantageous and deep learning methods. In order to minimize innate as well as suspicious things like single models, a new range of hybrid technique was introduced that mixes the advantages of several dissimilar single models. To achieve greater forecasting accurateness, a lot of evolutionary techniques (Sundararaj et al. 2018; Sundararaj 2016) are developed with DNN in recent years. Among them, a Genetic Algorithm (GA) was employed to obtain weights and optimal thresholds. From the implementation result, it is clear that the GA algorithm provides better accuracy but this approach was computationally expensive and time-consuming. The data gathered from several algorithms namely Particle Swarm Optimization Algorithm (PSO), Firefly algorithm (Vinu 2019), Simulated Annealing (SA) and Differential Evolution (DE) so as to design a Cuckoo Search (CS) algorithm (Chen et al. 2017) which provides better results when compared with other approaches. The CS algorithm has fast convergence speed when compared with the DE algorithm. Also, the cuckoo search algorithm has extra implementation capability than the particle swarm optimization algorithm (Vinu Sundararaj 2019). Apart from precision and stability in forecasting, the forecasting representation also contains better accuracy at each and every stage. Moreover, the cuckoo search approach also guarantees the security processes of the power system during forecasting the model. For stable operation, the Chicken Swarm Optimization (CSO) is proposed in this paper, which has the description of elevated exactness, express convergence time and superior steadiness. The chicken swarm optimization approach provides the estimated result with better efficiency at a limited duration of time.

To improve productivity and to overcome the above drawbacks of the optimization, the new technique is presented and actualized in the proposed strategy. In this paper, the DNN-CSO is proposed to solve the STLF problem-based ensemble approach in the wind energy system. The prediction of next hourly load data is attained by means of data pre-processing, normalization, data structure and learning error rate adjustment. The DNN is utilized to enhance system stability.

- The main contribution of the research work is to propose an approach for short term load forecasting in a wind energy system using the hybrid algorithm. The hybrid algorithm involves the integration of the Deep learning concept and the Chicken swarm optimization Algorithm for minimizing the RMSE and MAPE, respectively.
- Implementing the DNN-CSO method solves load forecasting problem thereby providing estimated results with enhanced system stability and better efficiency.
- Minimizing the training error rate by means of Chicken Swarm Optimization algorithm.

The paper is organized as follows: Sect. 2 describes the related research work. Section 3 provides a detailed description about the proposed load forecasting method. The processing of DNN network along with the CSO algorithm discussed in Sect. 4. Section 5 gives a clear view of graphical analysis with respect to various parameters. Finally, Sect. 6 concludes this paper.

2 Review of related works

Basically, wind power forecasting is achieved through many methods. The initial step of wind speed forecasting consists of wind power forecasting. Numerous methods were suggested and implemented in order to attain a load forecasting.

Sun et al. (2019) proposed a Predictive Distribution Optimization for solving the STLF problems; however, the most important process involves in the prediction of universal distribution for various conditions of wind. Barman and Choudhury (2019) have proposed a Firefly Algorithm (FA), Space Vector Machine (SVM) to incorporate the seasonality effect in STLF. This approach failed to consider computational complexity problems. Jean-Francois et al. (2019) demonstrated a Deep Learning-based Multivariate Probabilistic Forecasting. Moreover, this approach employed in reducing interface to the current set of information. Yadav et al. (2019) introduced the model amalgamation by combining the Adaptive Neuro-Fuzzy Interference System (ANFIS) and Genetic Algorithm (GA) for short term power PV solar forecasting. On the other hand, this approach was more complex in the case of season data and time-series data.

Hu et al. (2019) introduced the STLF model based on the hybrid GA-Particle Swarm Optimization (PSO)-Back propagation Neural Network (BPNN) algorithm. The performances seem to be complex in case of unfilled production. Wu et al. (2019) developed an amalgamation process of generalized regression neural network (GRNN). This approach contains a sorting that depends on a non-dominated sorting based multi-objective cuckoo search algorithm (NSMOCS) for STLF. This approach provides only less information about the characteristics as well as noise clean processes in short term load forecasting.

Peng et al. (2020) developed a novel ensemble approach and the wavelet soft threshold denoising (WSTD) approach along with the gated recurrent unit (GRU) concentrates more on filtering the redundant information from the raw data. Moreover, this approach provides better accuracy rate value with very high forecasting speed. This approach failed to track the computational complexity rate. Jiang et al. (2019) developed a multi-objective salp swarm optimization interval production process for designing a wind power forecasting model. Moreover, this approach fails to consider the troubles regarding atmospheric conditions. Also, this approach has a very high implementation cost. Zhang et al. (2019) introduced a chaotic search-harmony search-simulated annealing (CS–HS–SA) method to solve the STLF analysis. This approach also requires an examination procedure to gather more amount of information during training processes. Somu and Ramamritham (2020) proposed ISCOA-LSTM to analyze the load forecasting problem. This method failed to consider forecasting of real-time data characteristics. Hazra et al. (2019) developed GOA for load forecasting problems in the network. This method was acceptable to obtain the trapped solution of the local optimum. The overall performances of existing methods are reviewed in Table 1. From the above investigation, it was well distinguished that the Deep Learning method has several inconvenience issues that create a drawback in some approaches. The distribution of load forecasting is associated with tractability problem as well as contingent upon the number of situations. In order to overcome several technical issues such as forecasting of non-linear load, internal noise, and complex time-series data, computational complexity etc. the proposed system is structured.

3 Background information on DNN and CSO

3.1 Description of DNN

Generally, the neural networks are having the ability to find out the complex togetherness regarding the patterns of input and the objective for the detection. For analysis of the load forecasting problem, the efficient solution is the DNN of the system. The output of the DNN should be in linear or nonlinear based on the input data. This input data can also be considered as the output of previously designed DNN.

Table 1 Summarization of existing methods

Authors	Algorithm/technique	Drawbacks
Sun et al. (2019)	Predictive distribution	It was difficult to select a universal predictive distribution
Barman and Choudhury (2019)	FA-SVM	Computational complexity
Jean-Francois et al. (2019)	Deep learning	decrease the interference between the original data set
Yadav et al. (2019)	Hybrid GA-ANFIS	complex time-series data and season data
Hu et al. (2019)	Hybrid GA-PSO	It was hard to deal with the complicated nonlinear characteristics
Wu et al. (2019)	NSMOCS-GRNN	The internal noise characteristics and information was difficult to compute
Peng et al. (2020)	WSTD-GRU	High computational complexity
Jiang et al. (2019)	Multi-objective Salp Swarm Algorithm	Trouble in atmospheric conditions and high implementation costs
Zhang et al. (2019)	CS–HS–SA	Requires training process
Somu and Ramamritham (2020)	ISCOA-LSTM	Failed to consider real time data characteristics
Hazra et al. (2019)	GOA	Getting trapped in the local optimum solution

The organization of the neural network within the range can be obtained by the effective use of input–output data. The feedback can also be used to improve the performance of the complete work (Fan et al. 2019). In the proposed methodology, the DNN is utilized to attain the prediction process in the system. Subsequently, the DNN approach combines the multiple perceptions of traditional layers and the current pre-training established approach. The structure of the DNN network is illustrated in Fig. 1.

The autoencoder in DNN has two parts such as encoder and decoder operation. In the encoder, the operation states transfer the space high dimensional change of input data to space low dimensional change of that input data. The function of decoder involves in reconstructing of input codes. Based on the autoencoder approach, the pre-training of the DNN is achieved and the load forecasting problem was solved.

3.2 Description of the CSO algorithm

The hierarchal CSO order depicts the behaviour of a chicken swarm which is optimized based on the foraging behaviour of birds. The chicken swarm was classified into numerous groups such as one rooster in each group, several chicks and many hens (Wang et al. 2019a, b, c). The steps involved in chicken swarm optimization are elucidated as follows.

3.2.1 Steps of the CSO algorithm for optimization

3.2.1.1 Step 1: Initialization In this step, the chicken swarm, training error rate, and related parameters are initialized. Let us consider N_H,N_R, N_M and N_C as roosters amount, chicks, hens and mother hens successively. N and D can be the amount of chicken swarm and dimension of the search space respectively.

$$X_{a,b}(T)(a \in [1, \dots, N] \in [1, \dots, D]) \tag{1}$$

$$X_{a,b}(T+1) = X_{a,b}(T)(1 + \text{Random}(0, \beta^2)) \tag{2}$$

where random$(0, \beta^2)$ can be Gaussian distribution mean 0 and standard deviation β^2.

3.2.1.2 Step 2: Evaluation of the fitness Step 2 involves evaluating the fitness function of the optimization.

The fitness function is described in the below equation,

$$FF = \min(\text{Error}_L(\beta)) \tag{3}$$

Based on the fitness function the load forecasting problem is achieved.

3.2.1.3 Step 3: Assigning and determining the chicks in a random position In the CSO algorithm, the N_R is assumed to the best solution, N_C is assumed to the worst solution. The roosters having the best foraging ability and the largest foraging range were considered as a leading cock among the flock whereas, the chicks contain the smallest foraging range and worst foraging ability (Fu et al. 2019). In this step, the initialization of the personal best and global best position is attained. The mother–child bond randomly represents the chicks and the hens as mentioned in the below equation.

$$\beta^2 = \begin{cases} 1 & F_a \geq F_t,\ t \in [1, N], t \neq a, \\ \exp\left(\frac{F_t - F_a}{|F_a| + \varepsilon}\right) & \text{Otherwise} \end{cases} \tag{4}$$

3.2.1.4 Step 4: Renew the position Here, position renews of the roosters, hens and chicks are attained based on the above equation and the values are computed for individual fitness.

3.2.1.5 Step 5: Update the position Step 5 involves the updation of the best global solution and the best personal solution.

3.2.1.6 Step 6: Termination In termination stage, the iterative condition is $T = T + 1$, if it met the iteration condition then the iteration turns to stop where the iteration also stops the progress of the global export optimum; elsewhere it goes through the next procedure.

Based on CSO optimization, the training error rate is minimized. The DNN learning rate error is reduced to achieve the load forecasting problem in the wind energy system. This part explains the proposed concept for

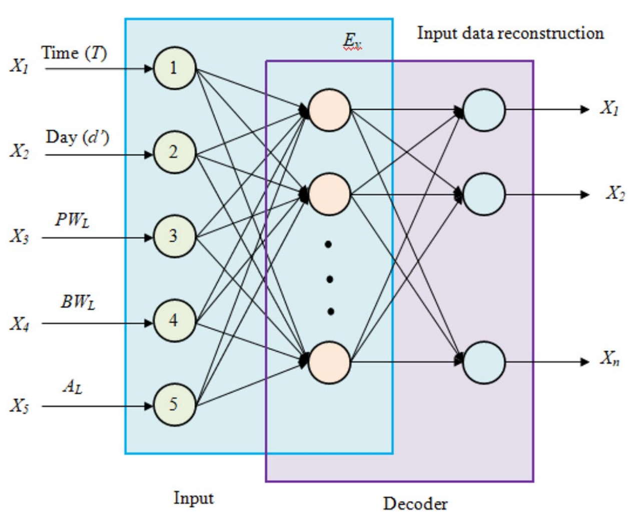

Fig. 1 Structure of DNN

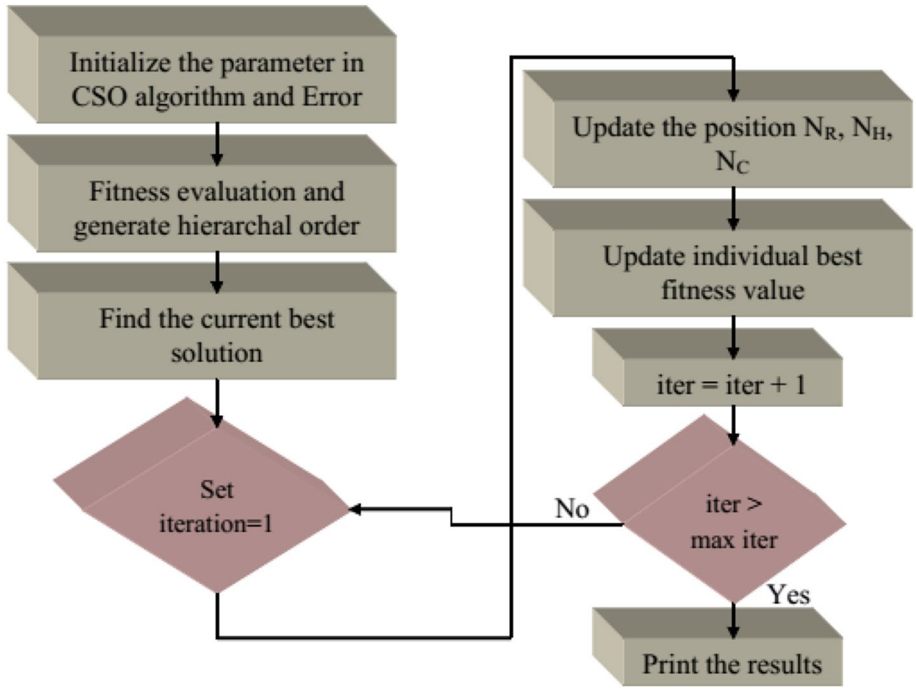

Fig. 2 Flowchart for the CSO algorithm

energy load forecasting with the usage of the DNN-CSO approach. The flowchart of the CSO is presented in Fig. 2.

4 Proposed DNN-CSO for Wind Power Prediction

4.1 Process of DNN-CSO

In the proposed methodology, the load forecasting is achieved with the help of the DNN-CSO hybrid algorithm. The DNN helps in predicting the load forecasting problems in the wind energy system. From the DNN structure, the training error rate is minimized with the consumption of the CSO algorithm. The training error rate is computed based on the actual load data to the target data in order to predict the next hourly data. Therefore, the error value is minimized and thus the load forecasting is achieved in the wind energy system. The above steps provide a clear description of each process involved in the chicken swarm optimization process.

The objective of the proposed methodology for the load forecasting problem can be achieved by calculating the energy load to the time-step for the future load by gathering the historical data of the wind energy system. The hourly data of the wind energy systems are computed from the New England ISO. The first autoencoder that was trained to be noted reduces the error that occurred during reconstruction. Therefore, a parametric set of initial trained neural network encoders is attained among the hidden layer of the DNN. The initialization of the first DNN hidden layer and the available initial encode vector predicts the hourly data which is expressed by the following equation,

$$E_V^1(X(T)) == E_{F1}\{X(0),\ X(1),\ X(2),\ X(3), \ldots, X(24)\} \quad (5)$$

where $E_V^1 X(T)$ describes the actual energy load for the time step T with the first data encoder vector. Then, the second hidden layer is initialized by the secondary auto trained decoder. This process can be continued up to the nth autoencoder in order to obtain a trained vector among the last hidden layer of the DNN structure. The DNN process of pre-training is completed by using the above procedure. The next step involved in the processing of the DNN model is a fine-tuning procedure. The output of the DNN model was calculated from the input signal. The load energy prediction in DNN for another 'n' time steps was obtained by the following equation.

$$\begin{aligned} E_V^1 X^*(T) = E_{F1}\{&X^*(n), X^*(n+1), X^*(n+2), \\ &X^*(n+3), \ldots, X^*(24+n-1)\} \end{aligned} \quad (6)$$

where $x^*(T)$ describes the forecasted energy or predicted load energy to the step time T. The predefined hourly data was given as the input of the DNN layer for analyzing the predicted load. Normally, the load energy description in data time-series was encompassed with the generation, load demand of the previous week, etc. It is known that the DNN contains the hidden layer, input layer, and output layers. On the other hand, the inputs are taken in the form of the above equation for solving the load forecasting problem. The inputs are fed to the input layer where these inputs will be forwarded through the set of hidden layers. The load data contains the date data, as well as initial prediction time, enters the input during the operation of DNN. The vector input can be entirely layer connected to DNN that was described as follows,

$$\text{Input} = \left\{ O_h,\ h(n),\ d(n),\ T(n),\ PW_L(n),\ BW_L(n) \right\} \tag{7}$$

where O_h represents the output from the input layers, $d(n), T(n), PW_L(n), BW_L(n)$ represents the day, time, previous week load and Load of 1 weeks back, respectively. This equation provides the initial weekend prediction for the time stamp. The hourly information of ten previous procedures is utilized as inputs for the computation of the next timestamp prediction. The information about time stamps for the 11th step time utilizes the hidden layer as input (Amarasinghe et al. 2017). The next procedure involves training a DNN, which is referred to as fine-tuning. This process uses an autoencoder as layer by layer to train the neural network. This training process solves any trouble or problem that occurs during short term load forecasting. The actual hourly data variable obtained from the STLF issue makes use of the output target and feature sets such as day, time, previous week load and load of 2 weeks back. After the training process, the operation of the DNN network was similar to that of the ANN network. The training error rate was minimized in the training phase by means of the CSO optimization algorithm. The expression in terms of training error rate and its optimization function was obtained in the following equation.

$$\text{Error}_L(\beta) = \sum_{T=1}^{n} \left((E_V^1(X(T)) - X^*(T) \right) \tag{8}$$

where $\beta = \{F1, F2, F3, \ldots, Fn + 1\}$ is the parameter set. The set parametric value β is updated in the following equation,

$$\beta = \beta - \chi \frac{(\partial \text{Error}_L(\beta))}{\partial \beta} \tag{9}$$

where Error_L denotes the entire error prediction of n hourly future data and χ denotes the rate of learning in a well-tuned approach. The training rate error is minimized with the help of the CSO algorithm. The CSO algorithm is developed to detect the error that occurred during the output. The error value is minimized with the help of the CSO algorithm.

4.2 DNN-CSO based wind power prediction

Normally, the forecasting of load plays a significant role in planning, generation, transmission, operation, and control of the power system (Hao and Chengshi 2019; Qin et al. 2019). Here, the proposed DNN along with the CSO optimization method was utilized to solve the STLF problem in the wind energy system. The STLF is used to compute the load flow analysis and also it helps to overcome the trouble that occurs during the operation of overloading. The electrical loads can be subjected to various types of factors. In this paper, the most important factors were analyzed. Initially, the input features in wind energy are provided to predict the system. The overall proposed methodology predicts that the performance parameters and the input of the DNN technique depend on the adaptive system learning method. Therefore, the training error rate was minimized with the help of the CSO algorithm.

Figure 3 describes the block diagram of load forecasting for the proposed methodology in the wind energy system. The block diagram describes various processes of DNN-CSO based wind power prediction. The stable operation of the system is attained by solving the load forecasting issues by means of DNN-CSO based on the wind prediction

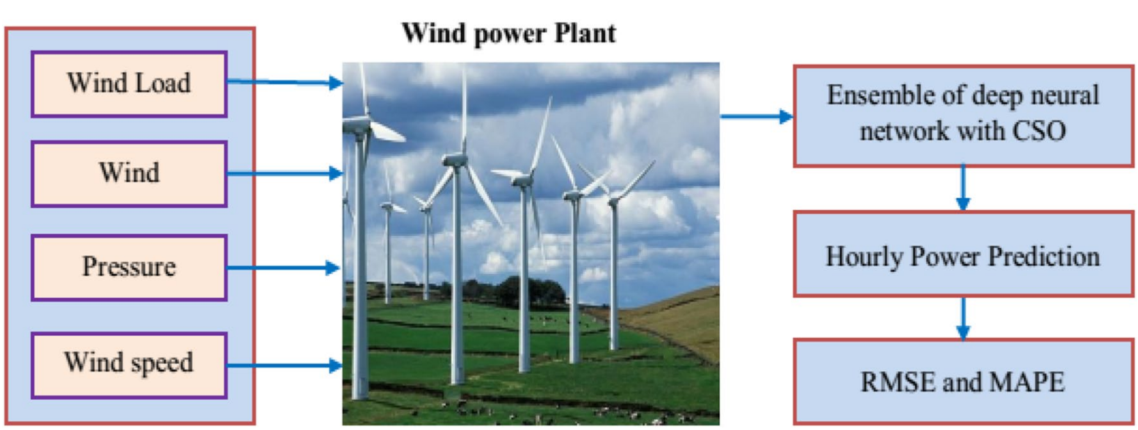

Fig. 3 Block diagram of DNN-CSO based wind power prediction

approach. The block diagram for DNN-CSO based wind prediction method and its design features are depicted in Fig. 3 in order to solve issues in STLF. The dataset of the wind energy systems is sent to the ensemble DNN for analysis of the load forecasting problem. Using the ensemble DNN method, the prediction is achieved. In this DNN network, the training error rate is minimized with the help of the CSO algorithm. Finally, the performance analysis of the suggested approach is calculated based on the evaluation index such as RMSE, MAPE.

4.3 Proposed framework

This section describes the proposed load forecasting system that utilizes DNNs as shown in Fig. 2. This framework describes the working flow for analyzing the hourly dataset of the wind energy system. Here, the load forecasting of the wind energy system is attained with the help of the ensemble approach DNN. The overall process is described in this section.

4.3.1 Data processing module

In this proposed methodology, the wind energy systems consist of data sets namely demand-side hourly data and power generation data for prediction purposes. Based on the wind energy systems, the data set consists of time, power consumptions, hourly load demand, etc. Moreover, the proposed methodology involves solving the prediction and load forecasting problem by means of the DNN controller. From this figure, the initial data are categorized into two databases such as customer load database and regional weather database (Chen et al. 2019). The customer load database collects the hourly load demand in the consumer side, respectively. Similarly, the regional weather database provides wind speed, wind direction, generated power, etc. Basically, the generated electricity from the wind energy achieves the load demand of a consumer. In the wind energy system, the rotational energy is converted into electrical energy. Here, the customer load database and weather database are collected from the New England ISO initially. In the data pre-processing section, the data are collected based on the hourly manner.

In the data pre-processing section, the hourly data was extracted from the New England ISO. Normally, the data pre-processing contains information about cleansing, normalization and structure alteration for load forecasting. The load measurements are detected from the data set that contains a few defective data, (for example, missing values and zero measured data are said to be known as defective data). In the data cleansing process, the missing and zero measured data can be changed by using the average or previous loads. After the completion of the cleansing of the data process, the data should be under normalization (Dozic and Urosevic 2019). In the normalization process, the data regarding weather are formalized to maximum value. The normalization process is achieved based on the below equation.

$$\text{Normalization} = \frac{\text{Raw attribute value}}{\text{Maximum value of arrtribute}} \tag{10}$$

The informative training has a large value but the required matrix weight seems to be extremely small in attaining the sum weighted within the suitable range of input for the activation of sigmoid function. Conversely, it is found to be extremely hard to utilize the BP algorithm by means of small weight. Therefore, normalization or renormalization of weight is required in the database in order to obtain valid load forecasting prediction results. The training data contains the input values of the DNN and the desired output value that calculates the prediction error values. Let us consider an illustration; Load model for 24-h forecasting is taken into consideration to attain a normalized load profile. Here the input of the wind energy contains information about past generation, consumption, parametric weather such as a month, date, wind direction, etc. Then, the data intended for the prediction of load forecasting was sent to the training process of the DNN network. Based on Fig. 4, the data are extracted in the data pre-processing stage for training and testing the data. This training and testing process helps in attaining and solving the load forecasting problem. After the training process, the data gets shifted to the DNN forecasting section for forecasting of the load.

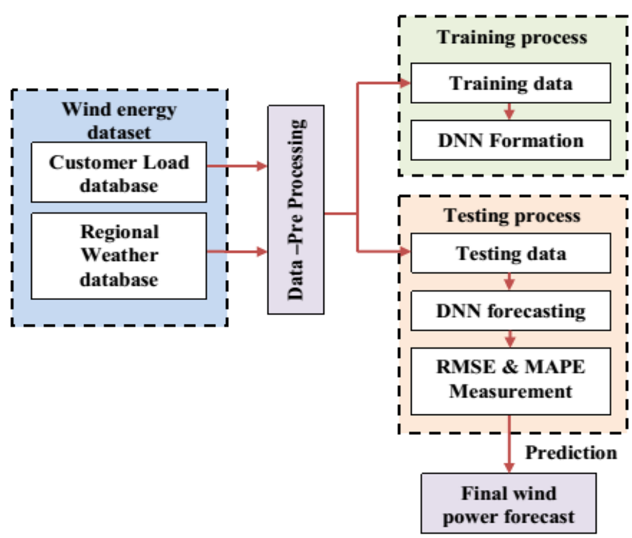

Fig. 4 Steps involved during processing of load forecasting

4.3.2 Training module

The training module involves training of the DNN controller for prediction and load forecasting models based on the input data. The data training enters the DNN module training only after the computation of testing and training data from the data pre-processing module. The training process of the DNN is illustrated in Fig. 5. In this proposed methodology the training part plays a vital role in the computation of the load forecasting problem in the wind energy system. The DNN structure is explained in the below section. The DNN structure contains a number of neurons and hidden layers.

The input and the output layers of the training data have permanent dimensions and based on the number of neurons the load profiles are forecasted, respectively. In the DNN, every neuron layer produces the prediction value at the specific hour in the output section. The DNN structure requires training for analyzing the nonlinear data that relates the past observations and load profiles (Wang et al. 2019a, b, c).

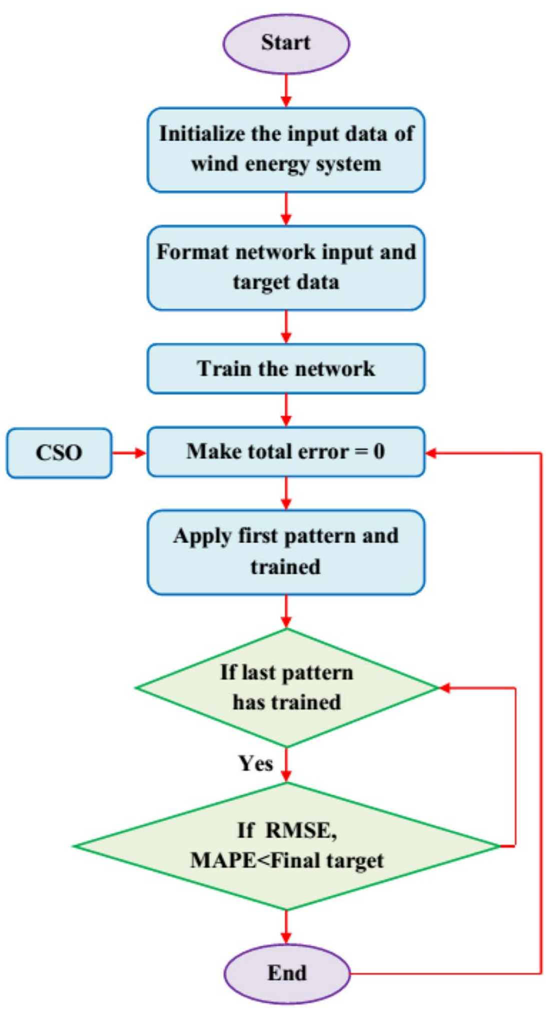

Fig. 5 Training process of the DNN network

From Fig. 5, initially, the data for the wind energy system is fed to the input. Based on the load profiles, the input and target data are computed. The training data error is minimized with the help of the CSO algorithm. Then the data was trained for prediction and load forecasting problem. The training processes were continued until the error value becomes zero. Once the training process ends, then the evaluation process is attained by means of RMSE and MAPE. The CSO algorithm process is explained in Sect. 4.1.

4.3.3 Forecasting module

The next process involves testing the data for prediction and load forecasting followed by the training section. The test information and the training data contain a similar structure. The testing process can be used to estimate the suggested model of forecasting. Practical expectations can be effectively acquired by replacing test information with past perceptions for targeting the forecasting dates. We build data validation from the data training and adventure validation errors as pointers for choosing legitimate variables (Jiang et al. 2018). The forecasting module is the final process in DNN-CSO based wind energy prediction model. The DNN is trained based on the input dataset. Then the input dataset of the DNN is fixed and it utilizes the training set for prediction by testing the day. For example, take 3 weeks of test days without considering the weekend, to predict the day d, the input is taken for days $d-5$ to $d-1$. Here, d alters from $d=1$ to $d=7$. The process of DNN is described in Fig. 3. Each and every week, new data was available for training. Similarly, each and every hour of 'n' previous days produces an output value (from the illustration) because the neurons are connected all over the network. The forecasting module assists in modelling several nonlinear relations such as inter-day nonlinear and intra-day loads during forecasting and training the next entire day based on relations trained. The accuracy model of forecasting is evaluated by means of the data test. The MAPE and RMSE are been utilized to measure the error occurred during the load forecasting. Based on the above process-based, the forecasting of the wind is achieved with the help of an ensemble DNN controller. The data analysis and processing of the proposed methodology are explained in the below section.

4.4 Data analysis

Analysis of the STLF is achieved with the help of the DNN technique. Initially, the dataset of the wind energy system is gathered from the New England ISO. The dataset consists of hourly load provided to the consumers for recent year records. From a dataset, five input factors are used to analyze the load forecasting in the wind energy system (Ozerdema et al. 2017). The five factors are selected for the hourly load (L/h). From the dataset, it is divided into two sets of categories such as training set and testing set. The factors are described below:

- *Time* Time of the day T, in hours and load L
- *Day* Day of the week d, and delivered load L
- A load of the previous week PW_L delivered a load L at a time d with time T
- Load of 2 weeks back BW_L delivered a load L at a time d with time T
- Average load A_L this is average of PW_L and BW_L

The coding of the attributes and inputs are described below:

- *Time* The range of time per day is (0–23 h)
- *Day* The range day of the week is Monday to Friday (7 days)
- *Load* Range between the 100 and 250 MW

The above load profiles are used to compute the load forecasting of the wind energy system is analyzed. The 24 h of wind load data is used for the analysis. The load forecasting analysis process is shortly explained by the way of the below steps.

4.4.1 Steps to be followed for load forecasting

Step 1 Initially, the raw data from the wind energy system are collected from the New England ISO.

Step 2 This step involves the pre-processing of data. Normally, it is necessary to have fresh data and it was pre-processed before modelling an input. The various methods of data pre-processing involve data cleansing, normalization and structure change for load forecasting. Followed by data cleansing, the data normalizing interval denoted as (0, 1) restricts the parametric model that dominates the usage of large and small data ranges.

Step 3 In Step 3, the data set follows the DNN procedure for training. The type of learning involved in the training was unsupervised learning that utilizes an autoencoder approach.

Step 4 In this step, the training dataset is tested. Here, the testing processes involve testing and validating the data of previous week available in the training set. The training error rate is minimized with the help CSO algorithm.

Step 5 In this step, the short term load forecasting utilizes the DNN-CSO algorithm in order to determine the wind prediction. Here, the STLF model is trained by means of the training set and the contrasted data forecasting sets validation to calculate the RMSE and MAPE of the validation set.

Step 6 Renormalization of the data sets can be found by evaluating RMSE and MAPE and it checks the condition for the proposed method analysis.

Step 7 Forecasting data was re-normalized and the output results were obtained.

Based on the above process, load forecasting of the wind energy system is achieved with the help of the DNN-CSO technique. The DNN-CSO is mainly used for the load prediction in the proposed methodology. The general process of the DNN-CSO is explained in the above section. To determine the proposed method, several performance parameters are tested with the evaluation matrix which is explained in the below section.

4.5 Analysis of the evaluation index of the proposed methodology

The error value is calculated based on the actual and forecasted value in the proposed method. If the forecasted load is very much greater than that of actual load, then the error value tends to be positive numerical. Similarly, if the forecasted load is smaller than that of the actual load, then there occurs a negative numerical error value. Normally, the performance analysis in terms of prediction and load forecasting in the wind energy system without losing the generality of the evaluation index is used for the computation process (Cao et al. 2012). The evaluation index is divided into two types such as root mean square error (RMSE) and mean absolute percentage error (MAPE). The major aim of an evaluation index is to calculate the accuracy of the suggested approach. The definitions of the index evaluation are described as follows,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\hat{x}_j - x_j\right)^2} \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{j=1}^{n}\frac{\left|\hat{x}_j - x_j\right|}{x_j} \times 100\% \tag{12}$$

where, n denotes the number of the data load series, x_j and $\hat{x}_j$ represents the actual and the forecasted values, respectively. To analyze or to compare the proposed method with the existing method (Hazra et al. 2019), the evaluation index involved in the computation process is shown below.

$$C_{\mathrm{RMSE}} = \left(\frac{\mathrm{RMSE}_2 - \mathrm{RMSE}_1}{\mathrm{RMSE}_2}\right) \times 100\% \tag{13}$$

$$C_{\text{MAPE}} = \left(\frac{\text{MAPE}_2 - \text{MAPE}_1}{\text{MAPE}_2} \right) \times 100\% \tag{14}$$

where C_{RMSE} represents the comparison of RMSE value, C_{MAPE}, represents the comparison of MAPE value, RMSE_2, represents index evaluation of the existing approach, RMSE_1 describes the index evaluation of the suggested approach, MAPE_1 denotes the index evaluation of the proposed concept and MAPE_2, represents the evaluation index of the existing method.

4.5.1 Condition for analysis

From the above analysis, it is clear that $C_{\text{RMSE}} > 0$, $C_{\text{MAPE}} > 0$, and this comparison clearly depicts that the proposed method is far better than the existing method, vice versa. There occur smaller differences among the two evaluation index if the values of C_{RMSE} and C_{MAPE} are close to zero. The performance parameters are analyzed and several performance metrics are better in DNN-CSO based wind prediction method when compared with the existing methods. The proposed method is implemented in the MATLAB in which the results are investigated in the below section.

5 Results and discussion

The performance of the proposed methodology is analyzed in this section. In order to authenticate the wind load forecast presentation, the proposed model is implemented in the Matlab/Simulink. First, the data set and model implementation are illustrated. Then, experimental results are demonstrated. For the implementation purpose, the dataset of the wind energy system is collected from the New England ISO. From this, the raw data of the wind energy system is collected which includes the dew point temperature, dry bulb temperature, humidity and system load. The dataset contains the above parameters with 24 h for prediction purposes. To train the network data, the data are separated into three parts, i.e. validation, training, and testing. The load dataset is feed to the DNN for training purpose. In the training process, the training error rate is minimized with the help of the CSO algorithm. The implementation parameter was mentioned in Table 2 and the sample data for 1 day is given in Table 3. In this section, the proposed method is tested using actual load and temperature data. Using the data of temperature and actual load data, the proposed method is tested in this section. To analyze the efficiency of the proposed method this is compared with the other existing methods such as DNN and ANN, respectively. The evaluation of the proposed method is measured with the way of metrics such as MAPE and RMSE, respectively.

Table 2 Implementation parameters

Algorithm	Description	Parameters
CSO	Max epoch	50
	Initial learning rate	0.005
	Learn rate drop factor	0.2
	Maximum iteration	1000
	Population size	100
	Dimension	20
	Update function of chicken	10
	Rooster population size	0.015
	Hen population size	0.7
	Mother hen population size	0.5
	Lower bound	− 100, 1
	Upper bound	100, 1
	Maximum iteration number	100
DNN	Initial momentum	0.5
	Learning step size	0.01
	Dropout rate	0.5
	Step ratio	0.01
	Batch size	0
	Optimizer	Adam
	Epoch	10
	No. of hidden layers	3
	Regularization strength	0.001
	Activation function	ReLU, linear
ANN	Input layer neurons	10
	Output layer neurons	1
	Learning rate	0.01
	Epochs	1000
	NN-type	Feed forward
	No. of hidden layers	1
	No. of iterations	1500
	Normalization range	[− 1, 1]
	Weight range	[− 100, 100]
	Bias range	[− 10, 10]
	Activation function	Sigmoid function

The brief description of the input data was elucidated as follows.

- *Dew Point Temperature*: It was basically a temperature value at which the air losses its control over the water vapour due to which some of the air molecules are converted into the water droplet and this particular temperature was lower than the temperature.
- *Dry Bulb Temperature*: Whenever the thermometer was used for the measurement of temperature then it is called dry bulb temperature basically, it was atmospheric temperature read by the thermometer whenever it was exposed in the surrounding.

Table 3 Sample data for 1 day

Date	Hours	Dew point	Dry bulb	Humidity	System load (MW)
1/1/2006	1	21.7	23.9	87.5	7726.892
1/1/2006	2	21.6	23.7	88	7071.833
1/1/2006	3	21.6	23.7	88	6685.44
1/1/2006	4	21.7	23.5	88	6487.837
1/1/2006	5	21.7	23.5	90	6388.927
1/1/2006	6	21.7	23.5	90	6494.333
1/1/2006	7	21.8	24	87	7062.48
1/1/2006	8	22.3	25.4	81	8037.868
1/1/2006	9	15.4	29.3	66	9169.365
1/1/2006	10	13.6	38.3	31	10,005.31
1/1/2006	11	13.2	40	23	10,463.6
1/1/2006	12	13.1	41.4	21	10,682.94
1/1/2006	13	12.6	42.7	19	10,842.33
1/1/2006	14	12.3	43.4	16	10,859.59
1/1/2006	15	12.5	43.8	16	10,900.74
1/1/2006	16	11.3	43.8	15	10,948.03
1/1/2006	17	12.4	43.2	16	10,997.9
1/1/2006	18	12	41.8	17	11,009.99
1/1/2006	19	14.1	39.3	23	10,894.9
1/1/2006	20	15.8	37.1	28	11,112.76
1/1/2006	21	19	25.2	69	10,247.09
1/1/2006	22	19.2	23.8	75	9345.815
1/1/2006	23	18.6	23.1	76	8416.873
1/1/2006	24	18.5	22.8	76	7737.28

- *Humidity:* It was nothing but a water droplet that represents the atmosphere but they were completely invisible for the human because it was basically a water molecule present in the gaseous state. As humidity increases, the ability of the body to resist the sweating capacity reduces due to a reduction in the rate of evaporation of moisture from the body.

The input dataset is feed to the proposed method to solve the wind load forecasting problem. Here, 24 h of the dataset is taken for the analysis purpose. The input parameters such as dew point, dry bulb temperature, humidity, and load are presented in Fig. 6.

Based on the above inputs, the load forecasting is evaluated with the utilization of the proposed methodology. The wind load forecasting is achieved with the help of DNN-CSO method. The process of the proposed method is training, testing, evaluation and comparison which is explained in the below section clearly.

5.1 Training and testing the data

The training process of the DNN is attained based on the input dataset. The training error rate of the DNN is minimized with the help of the CSO optimization algorithm. From the above process, the hybrid proposed approach is utilized to predict future loads for the wind energy system. The training process of the DNN is improved by means of a CSO algorithm. The DNN training uses Back propagation technique in which the original weights are arbitrarily certain in addition to the learning factor is prochoice. The presentation of the learning is extremely unstable sometimes owing to the collection of the learning factor. In the direction of discovering the optimal fit, the check and fault is common practice that runs the reproduction with dissimilar standards of learning factors. In this investigation, a greater boundary of learning factors is imitative from the use of CSO to reduce the training error rate. At iteration of arrangement training, the standard of loads is determined and a learning factor is characterized to fulfil the combination condition. The graphical analysis for the fitness value and the training data value is described in Fig. 7.

Figure 7 shows the plot analysis in predicting the actual load for various 7 days. The proposed method is used to predict the loads and it was analyzed based on the testing dataset. It is very well noted that the forecast burden bends for the proposed strategy that keenly tracks the actual burden for each and every time in a particular week. Based on reference, the testing blunder and the preparation mistake were compared by using the test spilled. Therefore, it was seen from the graphical analysis that the testing blunder was lower than the preparation mistake. It is necessary to attain a broad thought of calculation execution progressively. From the analysis, the testing dataset has a lower error when compared to the training error. Moreover, the proposed methodology predicts future loads more effectively. The testing condition of the proposed method is illustrated in Fig. 8. The presentation of the proposed method is analyzed by means of prediction analysis. Using the proposed method, the next 7 days loads are tested with the training dataset such as Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday, respectively. The training error is minimized with the help of the CSO algorithm for attaining load prediction with the best results and high efficiency. Then, the efficiency of the proposed method is compared with the existing techniques such as DNN and ANN, respectively.

5.2 Evaluation of proposed methodology

Load forecasting includes the estimation of future loads. The distinction between the assessed future load and real load is considered as a forecasting error. This paper focuses on momentary short term load determination, as members are

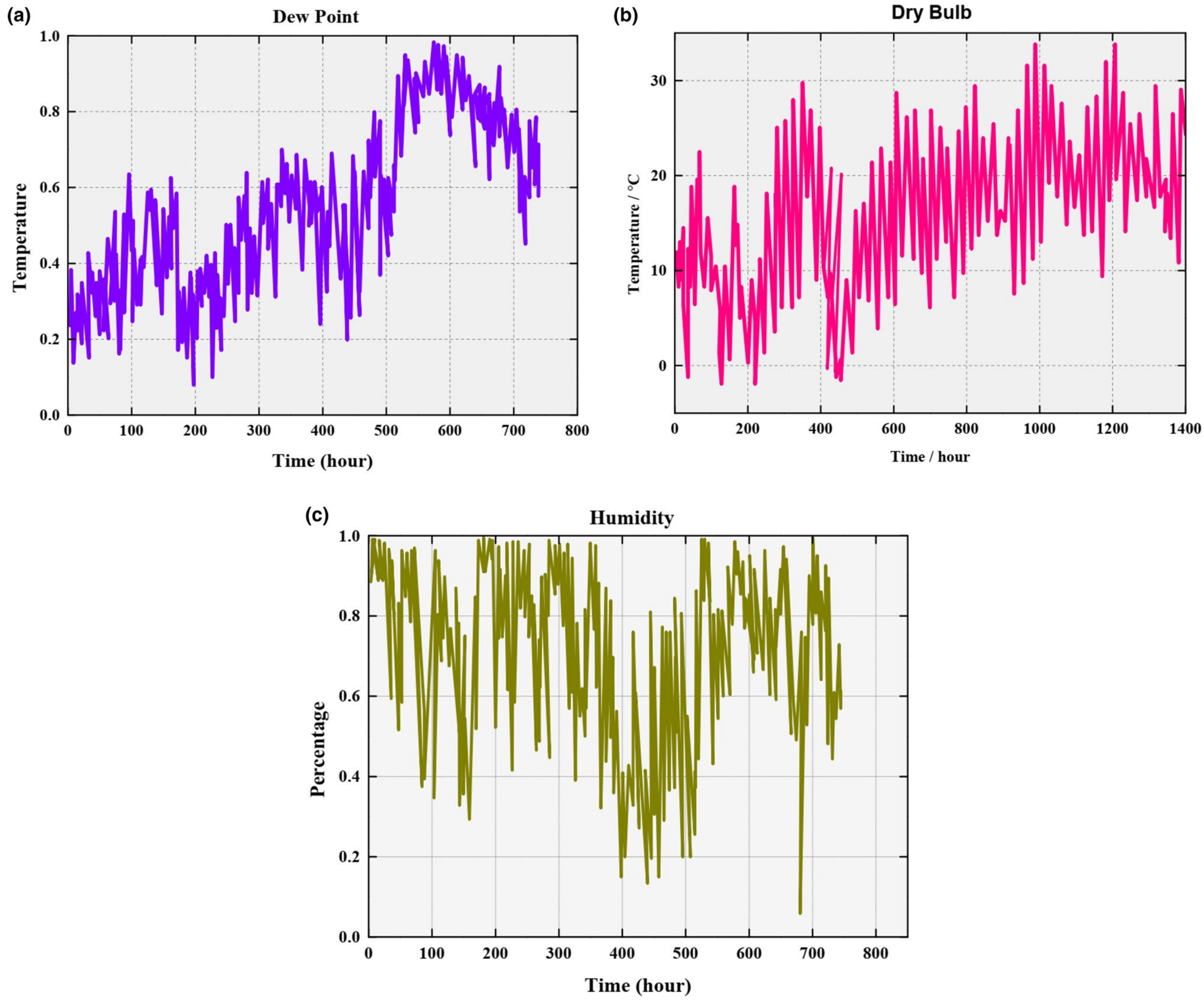

Fig. 6 Analysis of **a** dew point, **b** dry-bulb, **c** humidity

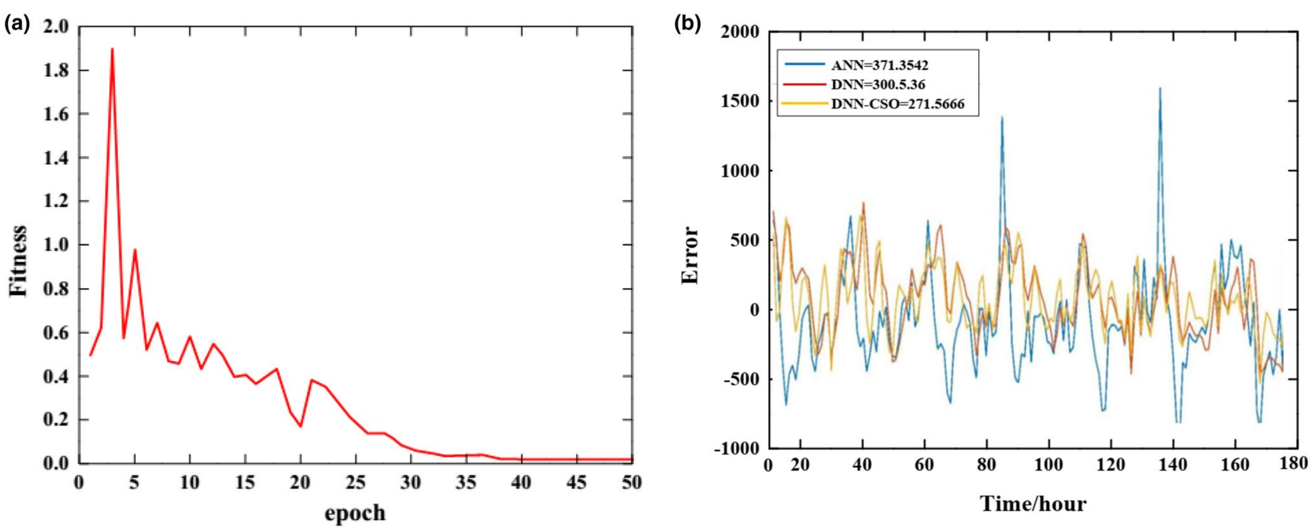

Fig. 7 Analysis of **a** fitness and **b** training error rate

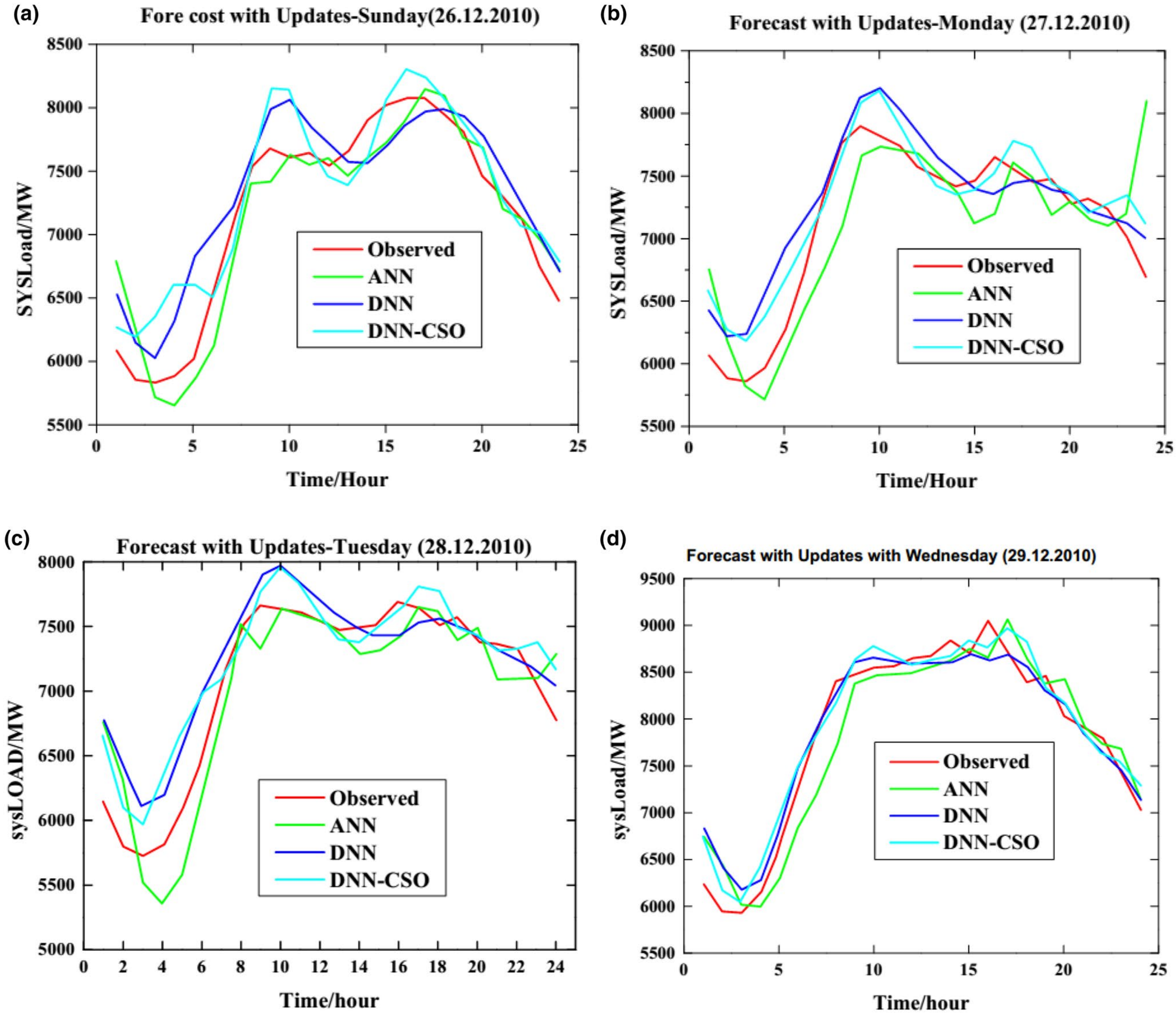

Fig. 8 Analysis of load prediction for various 7 days

increasingly worried about the hole between the pattern and genuine load accompanied by random changes in the atmosphere. The performance of any forecasting methodology can be evaluated using several proposed statistical metrics.

The MAPE and RMSE, along with response time are taken as assessment principles of expectation precision in this paper. The assessment of the proposed method is analyzed based on the evaluation matrix. The projected method is evaluated for RMSE and MAPE values which are illustrated in Fig. 9. Based on the evaluation matrix of RMSE and MAPE, the performance of the proposed method is evaluated and which are presented in Table 4. The analysis, the RMSE and MAPE are calculated for 24-h (1 day) load data of the wind energy system. The wind load forecasting is achieved more effectively by means of the proposed DNN-CSO based wind prediction method.

5.3 Comparison of proposed methodology

The evaluation of the proposed methodology is analyzed based on the evaluation indexes. For the efficiency purpose, the proposed method is compared with the existing methods such as ANN, DNN, ARIMA, and MLP. The predicted output of the RMSE and MAPE values are tabulated in Tables 5 and 6 respectively. Based on the analysis, the evaluation index of RMSE and MAPE are computed. For the efficiency analysis, the RMSE and MAPE are compared with the DNN, ARMA, MPL and ANN algorithms. It was seen that the DNN-CSO based wind prediction method contains

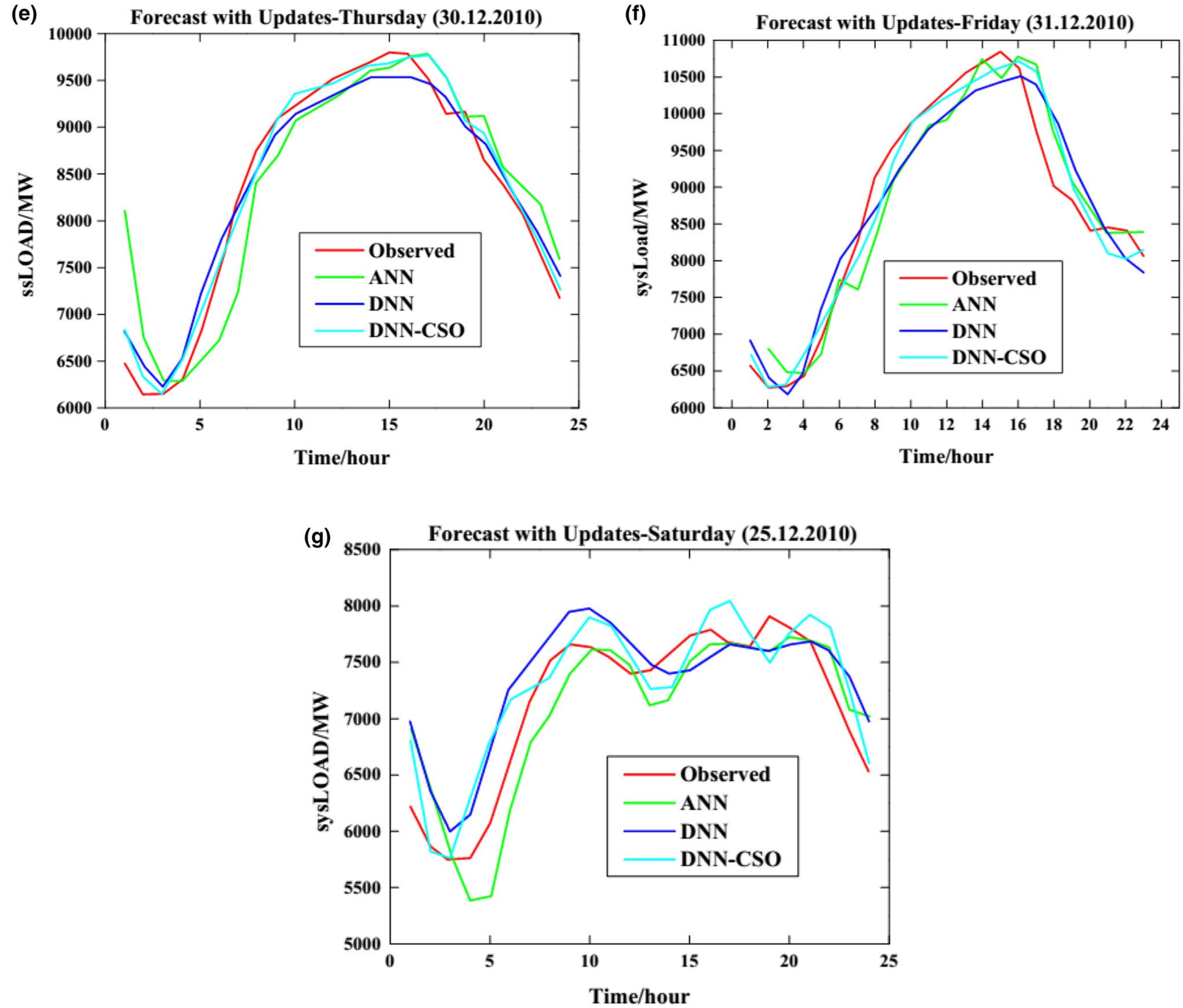

Fig. 8 (continued)

very least amount of error value rate of RMSE and MAPE, also the efficiency value obtained by this method is very high when compared to that of various methods like ANN, DNN, ARIMA, and MLP. For comparison purposes, proposed and existing methods are mentioned in the various colors and illustrated in Fig. 9a and b, respectively. Based on the datasets, the evaluation matrixes are computed for analysis of the performance of the proposed method.

Figure 10a describes the RMSE value for the proposed method, DNN, ARIMA, MLP and ANN, respectively. Based on the analysis, among the proposed method, DNN method, ANN, ARIMA and MLP method the proposed method has less RMSE error value. From this analysis, the proposed method has a higher efficient and accurate method for load forecasting in the wind energy system.

Figure 10b describes the MAPE value for the proposed method, DNN, ANN, ARIMA, MLP, respectively. Based on the analysis, the proposed method, DNN method, ANN method has a MAPE error value is 1.262857143%, 2.411428571%, 3.27285714%, 3.496% and 3.9832%, respectively. From this analysis, the proposed method has a higher efficient and accurate method for load forecasting in the wind energy load forecasting.

Figure 11 describes the predicted value with various loads for the proposed method, DNN, ANN, ARIMA, and MLP, respectively. Based on the analysis, the actual load condition was attained by means of DNN-CSO based wind prediction method. The error value between the actual load and the predicted load seems to be very large in the case of existing methods such as ANN, DNN, ARIMA, and MLP. From the analysis, it is proven that the proposed method

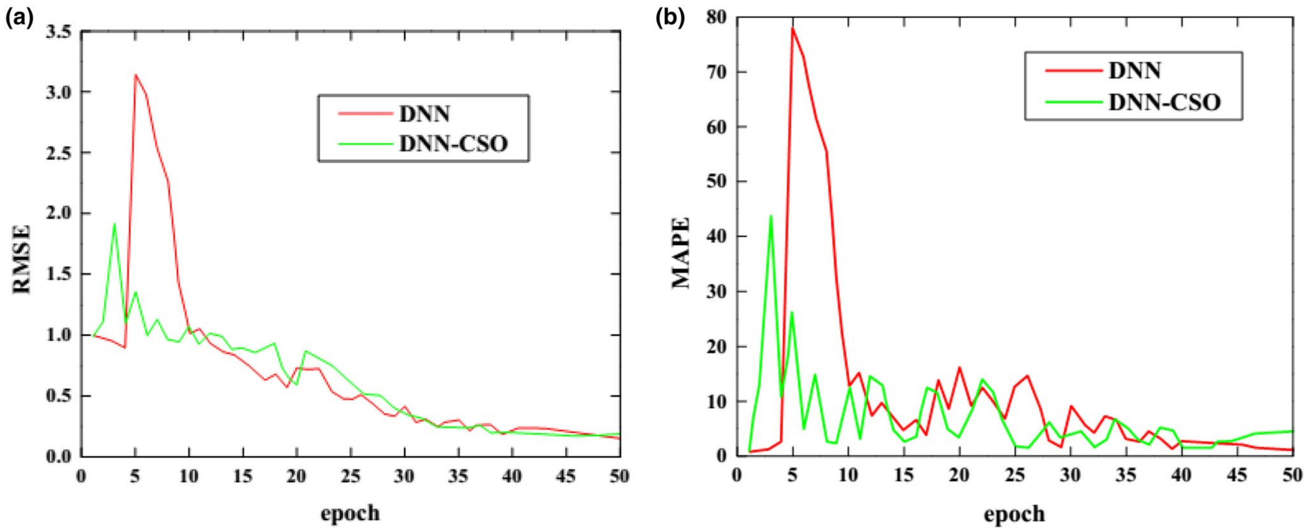

Fig. 9 Analysis of **a** RMSE and **b** MAPE

Table 4 Analysis of the RMSE and MAPE values

Time	Actual load	Predicted load	RMSE	MAPE
1	7726.892	76,235.13	1.00	0.58
2	7071.833	6872.241	1.25	35
3	6685.44	6599.98	1.08	42
4	6487.837	6422.38	1.56	15
5	6388.927	6377.987	2.0	12
6	6494.333	6491.33	1.66	26
7	7062.48	7010.32	1.15	15
8	8037.868	8037.12	1.72	10
9	9169.365	9100.169	1.58	0.5
10	10,005.31	9987.32	1.32	12.5
11	10,463.6	10,300.89	1.22	0.56
12	10,682.94	10,632.81	1.18	10
13	10,842.33	10,799.12	1.42	8
14	10,859.59	10,792.48	1.85	7.25
15	10,900.74	10,899.71	0.75	4.25
16	10,948.03	10,932	0.66	11.85
17	10,997.9	10,778.1	0.54	12.00
18	11,009.99	10,999.99	0.33	9.56
19	10,894.9	10,812.8	0.24	4.28
20	11,112.76	11,000.65	0.54	0.98
21	10,247.09	10,100	0.35	1.28
22	9345.815	9312.715	0.78	10
23	8416.873	8398.998	0.65	8.95
24	7737.28	7718.98	0.42	4.25

Table 5 Analysis of RMSE value

RMSE (%)					
Day	Proposed	DNN	ANN	ARIMA	MLP
Sunday	0.8	1.8	2.4	1	0.9
Monday	0.675	0.99	2.67	0.85	0.75
Tuesday	0.621	1.58	2.14	0.95	0.8
Wednesday	0.548	1.72	2.78	0.8	0.75
Thursday	0.325	2.45	3.01	0.65	0.55
Friday	0.2	0.87	1.99	0.55	0.47
Saturday	0.198	0.65	0.98	0.63	0.54

Table 6 Analysis of RMSE value

MAPE (%)					
Day	Proposed	DNN	ANN	ARIMA	MLP
Sunday	0.9	1.5	2.8	0.95	0.87
Monday	2.1	2.6	3.5	2.38	2.24
Tuesday	0.85	3.22	3.99	1	0.9
Wednesday	0.79	1.98	2.5	0.88	0.76
Thursday	0.81	2.55	3.11	0.75	0.68
Friday	0.91	2.98	3.89	1.95	2.74
Saturday	1.48	2.05	3.12	1.63	1.52

is an efficient method for predicting the future load of the wind energy system.

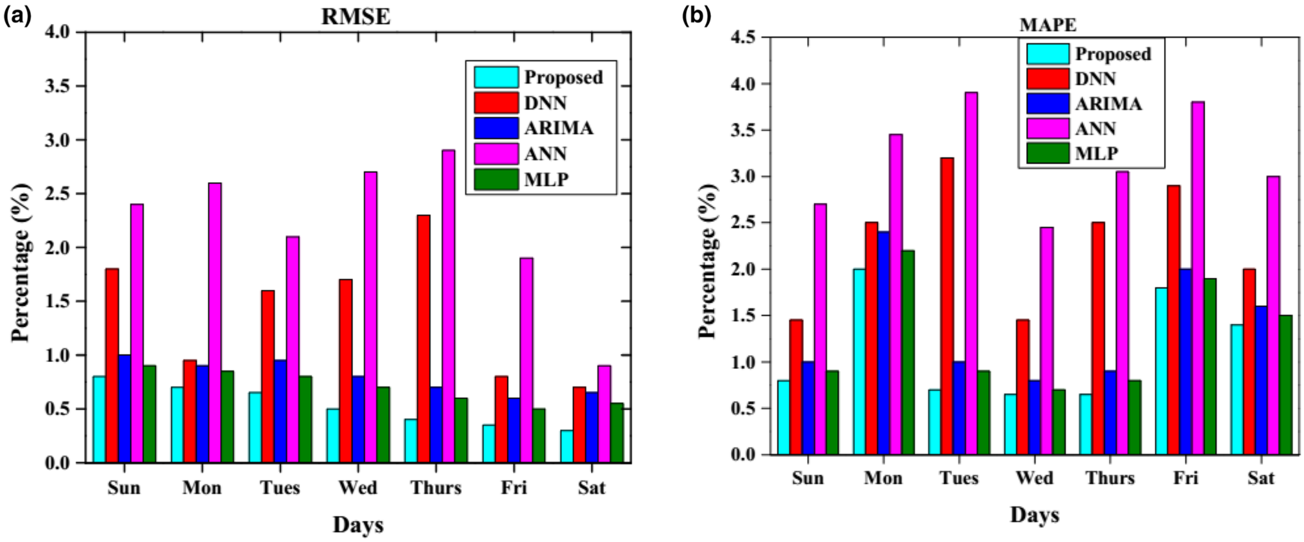

Fig. 10 Comparative analysis of **a** RMSE and **b** MAPE

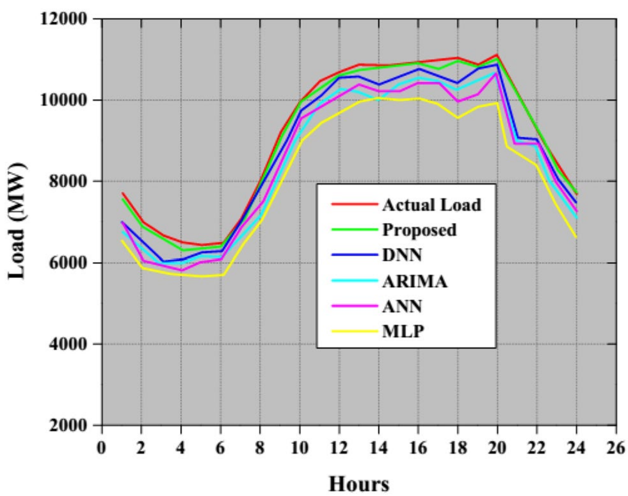

Fig. 11 Analysis of different loads

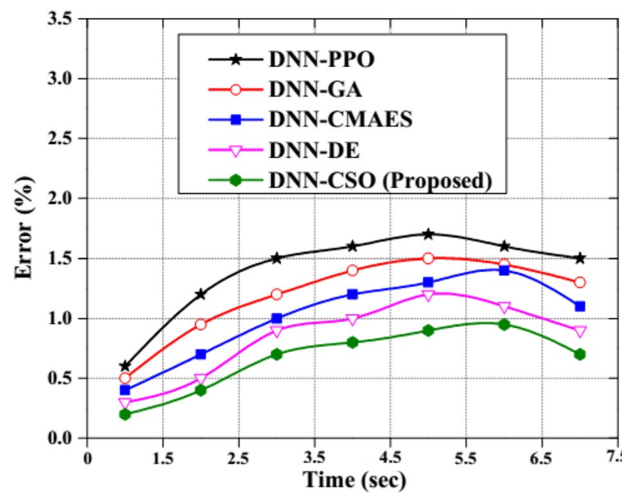

Fig. 12 Evolutionary analysis for error (%) vs time (sec)

5.4 Evolutionary analysis

The graph for evolutionary analysis was plotted for time v_s error in which the DNN is compared with the results of state optimizers such as CSO, CAMES, DE, GA and PPO. It is found that the error rate was very low in DNN-CSO based wind prediction method when compared to that of other optimization approaches. Here, implementation of the DNN-CSO method solves the load forecasting problem also it minimizes the training error rate as shown in Fig. 12.

6 Conclusion

The estimation of wind speed is considered a crucial issue in wind energy generation, transformation and activity, which has been drawing a ton of considerations. This paper has presented a hybrid technique utilizing an ensemble of DNN-CSO time series expectations that depends on STLF for wind speed forecasting. A proposed technique is trained and tested to give STLF based breeze load estimating. The historical information of time series regarding electric load and climate temperature is utilized for training the model that effectively provides 24 h determination.

The proposed technique has been tested utilizing real information from the New England ISO. Equally, 7 days and 24-h ahead load estimation is measured. The outcome showed that the proposed strategy create preferable forecasting precision over other existing models. Performance evaluation in terms of MAPE and RMSE shows that our proposed technique is better than previously reported techniques. At the point when contrasted and other well-known expectation models including ANN, ARIMA, MLP and DNN, the proposed hybrid calculation accomplishes a superior determining act with the base estimation of RMSE and MAPE individually. Sooner rather than later, multivariate time series expectation dependent on profound learning calculations utilizing increasingly interrelated highlights like climate conditions, human factors, and power framework status will be examined for progressively complex wind speed forecast. Then again, the creators will endeavour to think about progressively proficient outfit learning structures to advance the model forecasting capacity.

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