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Intelligent based hybrid renewable energy resources forecasting and real time power demand management system for resilient energy systems

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Abstract

The rapid growth of hybrid renewable Distributed Energy Resources (DERs) generation possess various challenges with inaccurate forecast models in stochastic power systems. The prime objective of this research is to maximum utilization of scheduled power from hybrid renewable based DERs to maintain the load-demand profile with reduce distributed grid burden. The proposed mixed input-based cascaded artificial neural network ($CANN_{MF}$) is realized for the prediction of a short-term based hourly solar irradiance and wind speed. The testing approach is performed through a historical hourly dataset of the proposed site. Further, the normalized data sets are divided into hourly-based samples for validating the load demand power with respect to the variation in metrological data. In this paper, Adaptive Neuro-Fuzzy Inference System (ANFIS) model is simulated for short-term power demand prediction. This adaptive methodology is an effective approach for load-demand management which is based on cross-entropy. It also confirmed that during testing, the forecasting mean error and cross-entropy are less than 5% under a specific time slap of an individual day. The regression analysis is performed through the time series fitting simulation tool at different time horizons. The performance evaluation of the designed model is compared with the multi-layer perceptron model. Simulation results display the proposed mixed input-based cascaded system has enhanced accuracy and optimal performance than the multi-output correlated perceptron model.

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Keywords
cascaded artificial neural network, distributed energy resources, fuzzy interface system, multi-layer perceptron, real-time demand predictive control

Introduction

Today's load-demand imbalance issues are being concerned due to the uncertainty and intermittent nature of distributed energy resources (DERs).[1] To accomplish the global energy demand, there is a necessity for conventional and non-conventional resources to be estimated in a more efficient manner using intelligent techniques for maintaining the load-demand profile.[2] Previously, most of the forecasting techniques are primarily based on econometric generation forecasts for load flow estimation analysis. In the early 20's century, conventional techniques were used such as data mining analysis, which was very difficult for load-demand prediction in complex power systems. In the last two decades, intelligent-based load demand estimation has been a significant field to permit power generation planning and power demand control in an efficient manner.[3] To increase the accuracy of the power generation prediction model, designed a correlation between the training data and the desired forecast output through a deep learning algorithm, and further through validation of real-time data set.[4]

In recent times the major concern has emerged for the development of smart energy systems like dynamic energy devices, multi microgrids, and nonlinear based loads in restructured power systems.[5] Later, the forecasting techniques mostly comprise deep learning analysis, evolutionary techniques, computational intelligence, etc. These technological advancements enhance the prediction of electric demand at regular intervals to ensure a better power system's reliability. Apart from renewable energy resources forecasting, also huge attention towards intelligent based forecast because of unpredictable variation in several environmental parameters like solar irradiance, ambient temperature, wind flow direction, etc.[6] Mostly, real-time energy management systems have non-linear dynamic systems, so real-time energy demand management is a complex task. The real-time forecasting of renewable resources inherently controls the power demands, which is varying with respect to time seasonal variation, and environmental factors. Various methods have been suggested in,[7] for real-time demand management which is divided into two major categories. Such categories are non-parametric and model-based methods, respectively. The non-parametric method is more economical than the model-based method.[8] Generally, intelligent-based methods have been employed to forecast generation as well as for power demand control. Thus, real-time monitoring can be implemented for an independent system operator (ISO).[9] ANN-based time-series forecast model has less accuracy, but it provides predictable consequences from seconds to a couple of hours, also it is found that the time series technique is capable of monthly solar irradiance and wind speed forecast

The forecasting models are designed for single or multiples transactions, these models have specific applications based on forecast horizons such as ultra/very short-term load forecast (U/VSTLF). The prediction of various parameters such as short-term load profile, peak load, contingency during transients, etc. using the U/VSTLF approach.[10]

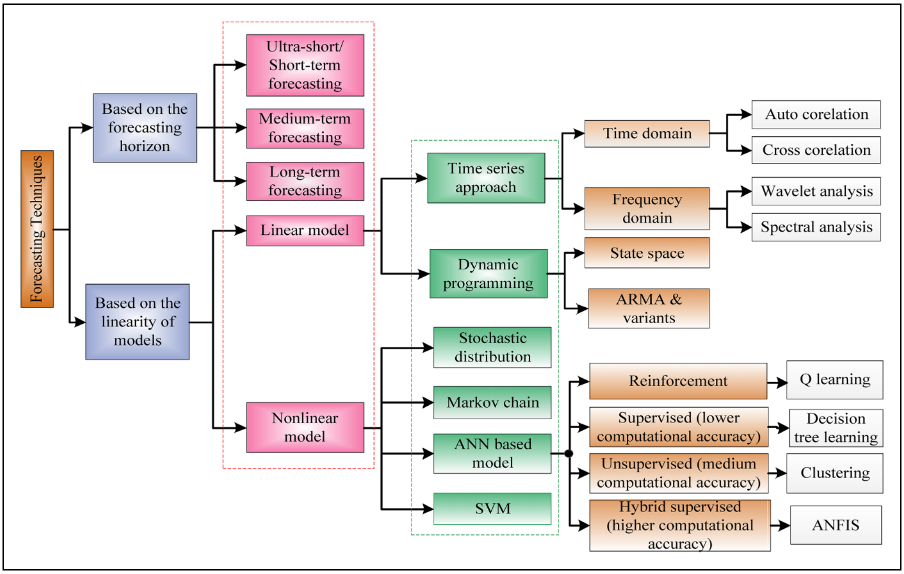

Figure 1. Classification of various forecasting models based on the type of time horizon with their learning capabilities.

The classification of various forecasting techniques is shown in Figure 1, short-term load forecast (STLF) technique uses for short-term weather parameters such as ambient temperature, wind speed, humidity, solar irradiance, etc. Further approaches were based on the auto-regressive integrated average model such as the support vector machine (SVM) model offers the forecast of short-term solar irradiance using practically measurement of short-term recorded data.[11] The medium-term load forecast (MTLF) prediction model is implemented for optimization and economic dispatch model[12] and the long-term load forecast (LTLF) model for the power scheduling management, real-time demand monitoring, estimation of available power transfer capabilities, etc. Table 1 is depicting the overview of the literature review in order to precise comparative analysis with various features of existing forecasting approaches and advanced techniques.

From Table 1, the performance of forecasting techniques can be evaluated for optimal DERs prediction for different time horizons. Also, comparative results of different time horizon metrics obtained the fitting algorithms such as linear regression during the next hour forecasting accuracy. In this paper, these results are compared and verified with the multi-layer perceptron (MLP) based short-term forecasting method. A recent study[37] has shown that intelligent-based forecasting of hybrid renewable energy resources for the prediction of dynamic energy generation. Short-term prediction of daily energy generation profile provides more accurate prediction based on predicted DERs value to ensure the real-time demand control.[38] In this paper, the main contribution is to design a high-accuracy framework based on the STLF for real-time electrical demand estimation and then validated the real-time data for the enhancement of the proposed intelligent framework. Further studies have shown in,[39] that the real-time hourly based STLF model is

Table 1. Literature review of existing forecasting approaches with advanced techniques.

Forecasting Techniques	Methods	Limited time scale Vary-short-term (VST), Short-term (ST), Medium-term (MT), Long-term (LT)	Key findings/ Outcomes	Feature applications	References
Physical forecasting techniques[13,14]	Single model	ST, MT	Single model-based load-demand estimation	Better physical models for DERs estimation and load demand management model	15
	Numerical weather prediction (NWP)	ST	NWP-based short-term wind energy prediction	High operational cost	16
	Persistence domain model	VST	A persistence domain-based scheme for GHI prediction on an hourly basis	Feasibility analysis for accurate GHI prediction	17
	Kalman filtering	ST, MT	Forecast of wind speed for hybrid power generation using Kalman filtering	Forecasted hybrid power generation for load-demand planning	18
	Maximum likelihood estimation	MT, LT	Solar irradiation estimation using satellite-derived data	The efficient output power of a PV system and unit commitment	19
Statistical forecasting techniques[20]	Time series-based auto regressive (AR) method	ST, MT, LT	An autoregressive scheme for spatial-temporal wind energy prediction	Effective autoregressive regression scheme for Load-demand	21
	Bayesian approach	ST	A Bayesian approach for short-term-based PV energy prediction	short term-based PV energy prediction using online/offline decisions	22
	ARIMA	ST	ARIMA overcome the limitation of the time series method for wind speed	Feasible for long-term wind speed prediction	23

(Continued)

Table 1. (continued)

Forecasting Techniques	Methods	Limited time scale Vary-short-term (VST), Short-term (ST), Medium-term (MT), Long-term (LT)	Key findings/ Outcomes	Feature applications	References
			prediction on the day ahead basis		
	ARMA	LT	Analysis of ARMA model for the mean wind speed	The regressive mean of DERs	24
	Distribution function model	ST, MT	Simulated statistical distributions functions for power demand prediction	Load reasonable decisions in the electricity market	25
Spatial correlation techniques[26]	Convolution neural network and Heuristic method	ST, MT	A heuristic approach based on estimating the hybrid energy resources	Active secure system for estimating the hybrid renewable energy resources	27
	Conditional kernel density estimation (CKDE)	MT, LT	Improved CKDE utilize an autocorrelation approach for hybrid renewable resource forecast	Optimal economic load-demand dispatch scheduling	28
	Gray forecast approach	VST, ST, MT	Estimation of future electricity consumption using the grey forecast approach	Regulation of DERs for real-time effective grid operations	29
	Empirical decomposition model	MT, LT	Performance assessment of empirical decomposition model for load demand prediction over time series approach	Decomposition model for load-demand prediction for higher time slap	30

(Continued)

Table 1. (continued)

Forecasting Techniques	Methods	Limited time scale Vary-short-term (VST), Short-term (ST), Medium-term (MT), Long-term (LT)	Key findings/ Outcomes	Feature applications	References
Optimization and Intelligence techniques[31,32]	Multi-objective-based optimization (MOBO)	LT	Enhanced MOBO approach for the renewable-based generation and load estimation	Modified MOBO for energy market clearing and operational cost management	33
	Hybrid intelligence model	ST, MT	A neuro-fuzzy-based model for PV forecasting in a smart grid	Effective for short-term power demand prediction with a higher learning rate	34
	Support vector machine (SVM)	VST	Wind speed estimation using SVM model with modified kernel functions	Long-term wind prediction with an enhanced region of convergence (ROC) plot	35
	Evolutionary optimization algorithms	ST	Short-term irradiance prediction using evolutionary optimization algorithms	Suitable for VST irradiance prediction using a differential evolutionary technique for nonlinear fitting	36

effectively employed in 20 zonal areas in the USA. The intelligent-based short-term forecast approach rapidly increasing in industries as well as the electrical power market because of the high system reliability and accuracy. The key contributions of the intelligent-based hybrid renewable resources forecasting, and real-time power demand management system are as follows:

- Design the multi-input layer based $CANN_{MF}$ model for hourly ahead solar irradiance and wind speed values. To get better testing accuracy on weekly basis, the system further utilizes the real-time data set to forecast short-term demand power on Mahidad (Gujrat state) India site.
- To demonstrate an ANFIS-based model having better learning capability for the development of a real-time load power management system.
- The advantages of the proposed methodology are described in the optimal power scheduling framework and developed for the centralized optimal real-time load-demand management system.

The rest of this manuscript is organized as follows. Section II discusses the modelling of the mixed input-based ANN model, ANFIS, and the proposed framework for a real-time power demand management system. In Section III, data collection and normalization in order to train the real-time short-term forecasting system. Section IV demonstrates the simulation results of the ANN-based technique for the proposed site (Mahidad, Gujrat, India). In the last Section V, comparative performance analysis and error evaluation during testing as well as validation period. Section VI is concluding with key findings as well as the future scope of the proposed forecasting system.

Forecasting models and power demand management system

In the modern stochastic power system, forecasts of DERs are an indispensable tool for increasing system reliability and real-time power demand planning and control. As the power system networks grow larger, consequently the uncertainty of various loads also increases which directly changes the total load-demand profile drastically. As a result, it began to be extremely hard to forecast the unpredictable load-generation management. The forecasting of solar irradiance and wind speed is vital for the effective usage of hybrid renewable energy resources. Nowadays, the exponential rise of smart energy systems, which are intelligent based control frameworks such as smart scheduling of distributed energy resources (DERs),[40] stochastic electrified transportation,[41] smart energy distribution systems, etc.[42] This research explained the computational intelligence-based forecasting opportunities for the development of resilient energy systems. In the present scenario, artificial intelligence-based microgrid development is an emerging model.[43] Also, the ANFIS technique is employed for real-time short-term forecasting, in which the training is based on ambient temperature data and variations in dynamic load.[44] The designed hybrid ANN model has better efficiency with a correlation coefficient of around 97 percent for short-term forecasting based on daily data, but that forecast model was too complex. Later on, several researchers demonstrated a comprehensive case study for the short-term solar power prediction and DERs generation control strategies based on a variation of several inputs parameters such as irradiance, aerosol content, humidity, temperature, etc.[45] Further evolution of intelligent scheduling techniques directly helped to balance power requirements with a more intelligent electrical power grid.[32] Still, the major challenge is the dynamic stability of the power grid due to uncertainties in renewable energy resources which are directly associated with several environmental changes and load variation. Unexpected variation in load-demand profile causes various power quality issues and power system stability degradation.[46] Thus, the future growth of the energy sector directly depends on effective and reliable forecasting operations for power generation entities as well as end-user customers.

In this paper, the main attention towards the restructuring of generation electricity companies (GENCOs) to develop the intelligent based DERs scheduling and further order to provide real-time information for generation side management as well as end customers. In[47] research has described the intelligence-based approach to mitigate real-time energy management issues for the development of optimal energy scheduling. On the other hand, several research works were carried out in order to describe the problem associated with the inaccuracy of forecasting techniques as well as load-demand balance. The annual energy outlook report (2021) has demonstrated the feasibility analysis of intelligent-based long-term forecasts.[48] The report shows the projections of electric power consumption to 2050 for G-7 countries (USA, UK, Japan, France, Canada, and other countries).[49] In,[50] presented the improved feed forward-based ANN architecture and design of their training algorithms. The testing result shows that the LM model accomplished a better prediction with minimum mean error. Therefore, the main reason behind his research is using the cascaded-based neural network technique because that system gets better learning capability to adjustable weight function during the training and validation dataset. To maintain the load demand continuously for a specific region, short-term forecasting using the ANFIS model with the uncertainty of several metrological parameters. Research in,[51] demonstrated that the ANFIS technique has a better capability of electricity forecast demand than the conventional autoregression technique. Further in,[52] research presented for real-time study of ANFIS-based load prediction using constant output function by utilizing comparative analysis of hybrid and cross-entropy techniques. Later in,[53] a case study of a large number of physical variables is fed into a hybrid neuro-fuzzy system and training was performed based on 23 years of previous data (1980–2003). Further, the validation phase was taken for the year of three-year data (2004–07). The major drawback of this forecasted system is that there was a very large number of training as well as long-term testing data required. The neuro-fuzzy model constraints are too complex, and the system may lead to inaccuracy. Recent research,[54,55] demonstrated the evaluation of deep learning in forecasting the wind speed for 30 min time resolution for London (UK), and Shiraz (Iran) case studies. The system validated the data set and achieved less accuracy than hybrid deep learning techniques in mean error results. Based on the outcome of these problems formulation, this paper implements the training data set of the solar irradiance/wind speed and further utilizes these energy resources in the power scheduling.

The forecasting of short-term renewable energy resources plays a vital role in the real-time DERs monitor for reliable and cost-effective microgrid operation. Intelligent-based real-time forecasting is a significant tool for daily peak load monitoring systems using short-term power demand prediction with time-varying from a minute to several hours.[56] This proposed system is suitable for hybrid (solar and wind) renewable energy-based micro-grid development, which comprehends the use of cascaded based short-term forecast of generation parameters and for the power-demand control using analysis of ANFIS technique. Alternatively, the wavelet neural network technique (WNN) can be implemented with either LM or GM models. But the outstrip of the WNN model needs modification for solar irradiance as well as wind speed forecasting. Therefore, the main reason behind utilizing the proposed cascaded technique is that it has a better and more flexible learning capability to adjustment in weight functions. However, the cascaded forward neural network architecture has dynamic flexibility during the training and validation period.[57] The efficiency analysis of both ANN and ANFIS models provides real-time demand distribution generation prediction for the generation. In the distribution generation site, a set of training data feed to the forecasted system. This data set is obtained from the testing site, which is based on several weather conditions and variations in environmental factors. The consideration of various environmental factors is very effective for accurate and long-term forecasting over a month as well as the prediction of a specific day.

Mixed input-based cascaded ANN network

In this section, a multiple-layer ANN is implemented based on supervised learning because it has the potential to characterize entire input data for forecasted data sets with output relationships. Also, if a large number of neurons is assigned in the hidden layer, then there will be a chance of a finite number of discontinuities. Generally, based on the learning horizon there are two types of ANN network flow i.e., feedforward or backward. A generalized and effective feedforward-based ANN is implemented with 2 hidden layers and each layer associating 10 hidden neurons to efficiently handle the correlated relationship between solar irradiance as well as other environmental variables such as ambient temperature, wind direction, pressure, humidity factor, cloud type, etc. Thus, the number of hidden layers, as well as neurons, were chosen by the trial-and-error evaluation approach to be tested. In this comprehensive study, the ANN with 2 hidden layers and each one having 10 hidden as the main structure of the existing MLP network with the initial layer estimator of the mixed input-based cascades artificial neural network ($CANN_{MF}$) network. The $CANN_{MF}$ model provides better results than the ARMA model for a forecasting horizon of short-term hourly ahead of time.[58] The $CANN_{MF}$ is employed for the forecasting of DERs in a short-term period of a complex system in order to get a suitable degree of accurateness with consideration of multiple environmental factors. When the normalized renewable resources data set is applied to the DERs forecast model. Here, the performance of the intelligent forecast model must be improved when compared with other forecast models during different environmental conditions. The $CANN_{MF}$ based technique is implemented to relate the optimal selection of suitable forecast parameters. The succeeding step is designed to get a suitable ANN-based training algorithm. Moreover, the back-propagation algorithm is usually employed for short-term forecasting.

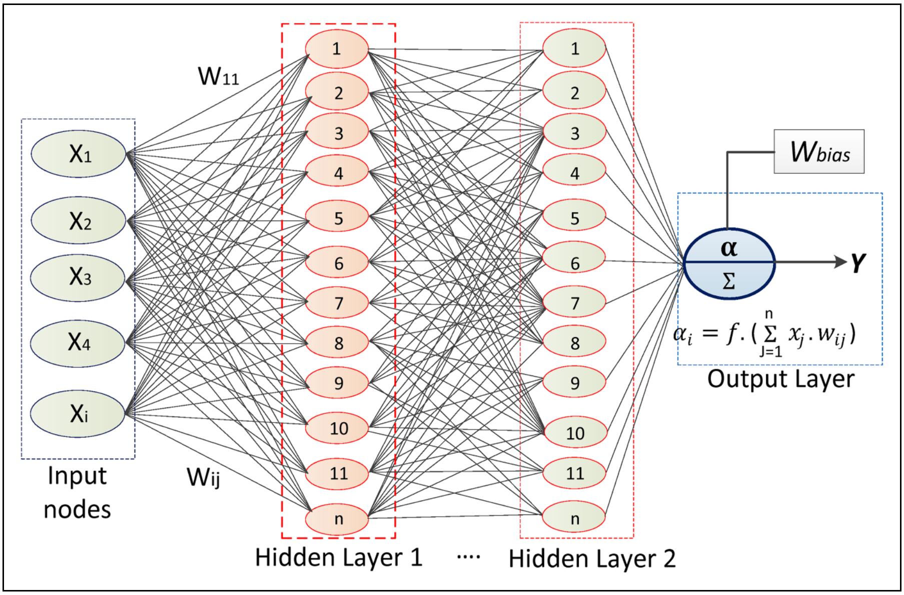

Figure 2. Architecture of feedforward ANN network with 2 hidden layers.

In Figure 2, the generalized inputs are fed through a certain weight limit in ANN architecture. The first layer signifies as (x_1, $x_2 \ldots$, x_n) of the input layer. In this layer, input variables are fed to the ANN network with appropriate weighted functions (w_{11}, $w_{12} \ldots$, w_{ij}). As per the differentiation condition of the respective activation value, every neuron has an individual activation function (f). These input weighted variables are exceedingly interrelated to the targeted output. The next layer signifies a hidden layer, and the last layer is the output layer which gives the desired output (Y). Before starting the training procedure, the raw data set is classified for training, validation, and testing purpose to obtain the output signals under various meteorological scenarios using the normalized data set. Once the data is classified, then the hidden layers are selected as per the regression plot. Before starting the training procedure, the raw data set are classified for training (70%), validation (15%), and testing (15%) purpose to obtain the output signals under various meteorological scenarios using the normalized data set. Once the data is classified, then the hidden layers are selected as per the regression plot. Once the ANN network is trained, then the w_{ij} and w_b values are regulated by changing the conjugate of the gradient algorithm. The Levenberg-Marquardt (LM) is the most popular training algorithm, which is the combination of the gauss-newton and steepest descent technique.

$$X_{k+1} = X_k - \frac{J^T.e}{[J^T.J + d.I]} \tag{1}$$

From Eq. 1, X is a training weight, d is the damping factor, J is a Jacobian, I is an identity matrix respectively of the 1st order derivatives of the ANN network errors.

The weights (w_{nn}) with biases (w_{bias}) is associating and the vector of processing errors is denoted by e. Therefore, if d is zero, then LM changes to Newton's method. While, if d is a higher value, then the LM changes to the gradient descent (GD) with a lessor step size. Therefore, the LM has a higher processing speed than the Gauss-Newton-based method. On the other hand, stability enhancement is achieved in the steepest descent method. Hence, here the LM-based backpropagation function algorithm is employed. During validation, if the error is not varying that means there is no variation occurring in the mean square error (e_m), in each instance. The overall performance of $CANN_{MF}$ the system is based on the comparative analysis of estimating error for the change in input variable shown in Eq. 2. In this study, all the errors are calculated in percentages for the forecasting of solar irradiance and wind speed on the proposed site.

$$|e_p| = |y_m| - \widehat{|y_m|} \tag{2}$$

Here, y_m is the measured DERs values and $\widehat{y_m}$ is the forecasted value for the step point (P), while Q is the total step point. The mean absolute percentage error (e_a) is represented in Eq. 3.

$$e_a = \frac{1}{Q} \cdot \sum_{p=1}^{Q} |e_p| \times 100\% \tag{3}$$

$$e_r = \sqrt{\frac{1}{Q} \cdot \sum_{p=1}^{Q} |e_p|^2 \times 100\%} \tag{4}$$

Mathematical evaluation of root means square error (e_r) is shown in Eq. 4. For short-term forecasting analysis, regression is a significant tool, which specifies the rate of change in predicted P_{ab} variables with respect to trained reference variables T_{ab}. The correlation represents the relation between more than one variable, which is correlated with another variable. Mathematically, the calculation of the correlation coefficient is as follows in Eq. 5.

$$C_{coef} = \sqrt{P_{ab} \times T_{ab}} \tag{5}$$

This proposed neural network-based approach has two stages: The first stage is the training stage, in which six months data set is taken as input to $CANN_{MF,}$ which has further utilized a multi-layer feed-forward algorithm. Where data set of points ($x = a_i, b_i$) as presented by m and initial guess (λ) for curve fitting model f (a, λ) during DERs training referred to in Eq. 6.

$$S(V_i) = \sum_{i}^{m} [b_i - f(a, \lambda)]^2 \tag{6}$$

And the second stage is data normalization so that raw data must be normalized and further feed as an input to the $CANN_{MF}$ for training and testing.

ANFIS based power-demand cross-entropy model

The ANFIS has utilized the various features of a hybrid neuro-fuzzy-based FIS system that comprises the parallel computation of ANN with their controlled learning capabilities. In,[59] the ANFIS model is effectively utilized for short-term load demand forecasting under various factors that affect the generation in grid-connected systems. These factors are based on time and random effects, respectively. Thus, the cumulative load-demand characteristics are dynamic varying in nature.

The ANFIS model signifies the probabilistic-based approach which is employed for the prediction of various uncertain variables that comprises the overall system's performance.[60] Here, Sugeno is considered for Fuzzy Inference Systems (FIS), which has the capability to recognize the various non-linear system response characteristics. From Figure 3, the adaptive node output of the first layer (fuzzification layer) depends on several evaluation parameters such as A_i, B_i and C_i are shown as follows in Eq. 7.

$$O_i^1 = \mu.A_i(x) = \frac{1}{\left[\dfrac{1}{\left[1 + \dfrac{x - C_i}{A_i}\right]}\right]^2} \tag{7}$$

where, $i = 1, 2 \ldots n$ and $(0 < (\mu.A_i(x) < 1$ for Gaussian curve). In the second layer, the adaptive node output is generalized by the multiplication of coming signals as referred to in Eq. 8.

$$O_i^2 = \mu.A_i(x) \times \mu.B_i(y) \tag{8}$$

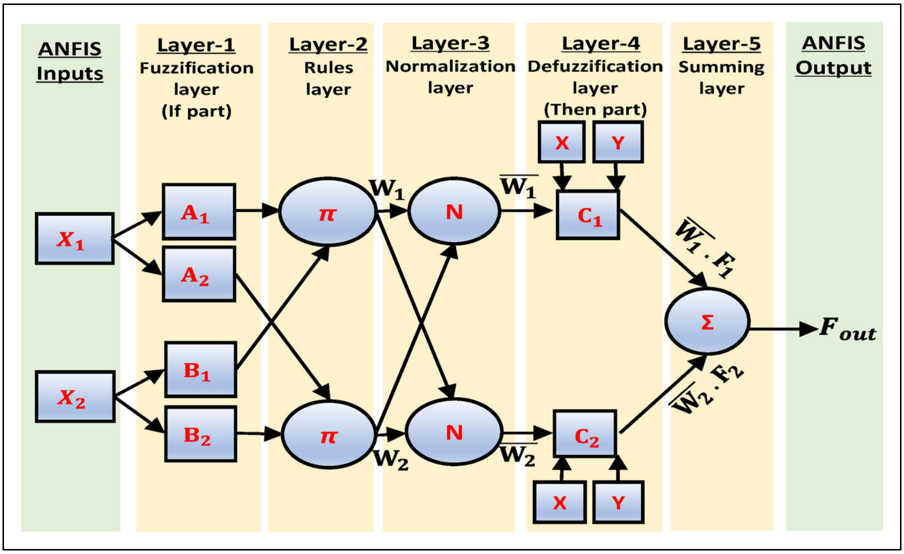

Figure 3. Proposed ANFIS architecture.

The third layer is associated with a normalized value (N) during execution. So, the output of the individual node is expressed in Eq. 9.

$$\bar{W} = \frac{W_i}{W_1 + W_2} \tag{9}$$

The next layer is the defuzzification layer, where every node is treated as a square node. Mathematically, the defuzzification layer is represented by Eq. 10.

$$O_i^4 = \left(\frac{W_i}{W_1 + W_2}\right) \times f_i \tag{10}$$

Finally, the last layer is the summing node, which is the addition of all incoming signals and further proceeding to get desired output. In Eq. 11, n is the number of neurons in layer 4.

$$O_i^5 = \Sigma_i \bar{W}_i . f_i = \frac{\sum_{i=1}^{n} W_i . f_i}{\sum_{i=1}^{n} W_i} \tag{11}$$

Moreover, the triangular membership functions (MFs) are selected because of their minimal execution time for a real-time load-demand management system.[61] From the perceptive of MFs response analysis, the computational capability is essential to check the learning phenomena. Therefore, the same MFs are chosen for demand-side management using $\Delta P_{demand}, \frac{d(\Delta P_{gen})}{dt}$ and FIS output segment. If the variation of scaling factors gets influenced by adaptive learning capability then there must be adjustment in the structures of MFs is required.[62]

Objective functions and system constraints. Due to changes in the metrological dataset, the adaptive system is providing the distinct capability to influence the execution of MFs for fuzzy controllers. As a result, the proposed FIS system is employed for enhancing the standard rules base. So that the control of real-time load-demand variations is achieved to increase the designed system performance. But the real-time data set are fluctuating regularly, which is further changed into the two additional parameters (peak power demand and available generation). In Table 2, the adjustment in rules bases is classified into the five sets (0–4) using the assumptions of generalized rule. Minimizing the $P_{uncontrolled}$ is subjected to in Eq. 12.

$$P_{load}^{min} \le P_{load} \le P_{load}^{max} \tag{12}$$

This real-time-optimal system model satisfies the entire constraints. These optimal solutions are achieved by the coefficient's functions for demand, generation, and controlled power in Eq. 13.

$$P_{demand}^{min} \le P_{demand} \le P_{demand}^{max}; \ P_{generation}^{min} \le P_{generation} \le P_{generaton}^{max}$$
$$\text{Subjected to; } P^{min} \le P_{Controlled} \le P^{max} \tag{13}$$

In Figure 4 the MFs of FIS assigned for input (P_{demand}), and output ($\frac{d(\Delta P_{gen})}{dt}$), the centre of gravity is employed for defuzzification, and FIS is implemented in the MATLAB

Table 2. Proposed FIS logic rule base.

$\frac{d(\Delta P_{gen})}{dt}$	ΔP_{demand}							
	NB	*NM*	*NS*	*ZR*	*PS*	*PM*	*PB*	Set-0
PB	ZR	PS	PM	PB	PB	PB	PB	Set-1
PM	NS	ZR	PS	PM	PM	PB	PB	
PS	NM	NS	ZR	PS	PM	PB	PB	Set-2
PS	NB	NM	NS	ZR	PS	PM	PB	
NS	NB	NB	NM	NS	ZR	PS	PM	Set-3
NM	NB	NB	NB	NB	NM	ZR	PS	
NB	NB	NB	NB	NM	NS	NS	ZR	Set-4

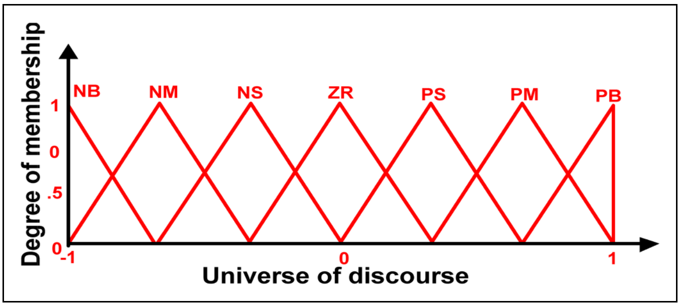

Figure 4. Membership function of FLC.

toolbox. The fitness function (J) is essential as a numerical capacity to reach and closely settle a specific problem for the proposed system. J is validated by variables using an optimal controller that is achieved to the pre-desired criteria, i.e., minimize the generation and minimize the fluctuations in the load-demand curve as referred to in Eq. 14.

$$J = \int_{0}^{Pmax} \left(w.(\Delta P_{load})^2 + \frac{1-w}{P_{demad}} (\Delta P_{load})^2 \right) dt \tag{14}$$

In Table 2, the fuzzy rule base variables within the range of [-1, 1], which signify as Negative-Big (NB), Negative-Medium (NM), Negative-Small (NS), Zero (Z), Positive-Small (PS), Positive-Medium (PM), and Positive-Big (PB). Generally, power demand control provides enhanced results for non-linear systems and also delivers the system instinctive from the fuzzy rule base.[63] If ΔP_{demand} is + ve and $\frac{d(\Delta P_{gen})}{dt}$ is $+ve$ then the output should be "+ ve" i.e set-0, while if ΔP_{demand} is *-ve* and $\frac{d(\Delta P_{gen})}{dt}$ is $+ve$ then output should be "zero" i.e. set-1.

In Table 2, the Set-0 demand power variation (ΔP_{demand}) and $\frac{d(\Delta P_{gen})}{dt}$, which are having extremely small positive or negative values that have a rule base essentially to interrupt real-time load-demand management. While in the Set-1, the ΔP_{demand} is negative high or medium then $P_{load} > P_{demand}$. Therefore, $\frac{d(\Delta P_{gen})}{dt}$ value is yielded to be the steady-state set of points for the FIS training network. Thus, the FIS controller indicates that the system is adjusted for the desired set of points. Under Set-2, the ΔP is close to the setpoint (NS, ZR, and PS) and lower than (PM, PB). Since the $\frac{d(\Delta P_{gen}}{dt}$ is negative the system yield, which is altered from the set of points. Thus, consequently, a positive controller to get the whole grid system under $P_{load} \gg P_{demand}$. While in Set-3, ΔP_{demand} is positive (medium or higher) value. Thus, the proposed forecasting response is far below the assigned set of points. That instant, $\frac{d(\Delta P_{gen})}{dt}$ is negative the system response which proceeding to the set of points ($P_{demand} > P_{load}$). In Set-4 the ΔP_{demand} is close to the set of points (NS, ZR, PS, NM, NB). As $\frac{d(\Delta P_{gen})}{dt}$ is negative the system yield, which is transferred from one set point to another. Thus, positive functions are needed for different demand levels to design the rule base system yield adjustment followed by a set of points. The description of the system operator, implication and FLC defuzzification showed in Table 3. The experimental fuzzy rule base for the proposed power-demand control system is as follows:

A proposed framework of real-time demand management

In,[64] a comprehensive analysis of a neuro-fuzzy adaptive algorithm is presented for the hourly basis forecasting of energy management using short sample time-series data. That has a specific FIS rule base on real-time demand management. On the other hand, due to a small variation in the generation side, STLF forecasting accuracy reduces under the implementation of multi-layer sub-processing units. The Intelligent based forecasting of DERs (solar irradiance and wind speed) is the furthermost cost-effective as well as positive means of assimilating the utilization of clean energy into the utility. The forecasting of solar irradiance, as well as wind speed, is essential for ensuring consistency in hybrid restructured power systems operational because these resources are associated with an appreciable degree of meteorological penetration. The proposed framework can be compatible with Distribution Electricity Companies (DISCOs) to enhance their monitoring ability during peak demand. As a result, the effective usage of renewable energy-based power generation (solar and wind power) can be enhanced for the shift of peak load demand to a significant level. Therefore, the real-time demand management system is more compatible rather than conventional independent system operator (ISO) control.

Table 3. Description of proposed fuzzy inference system.

Fuzzy Inference System (FIS)	Description
'AND' FIS operator	minimum
'OR' FIS operator	maximum
No. of inputs	4
No. of outputs	1
Implication method	minimum
Aggregation method	maximum
Defuzzification type	Centroid type
Number of fuzzy rules	49

The real-time power management system is subdivided into three major processing units, which are referred to in Figure 5. The first stage is the data collection unit for DERs forecast, which is an initial processing unit. Generally, short-term forecasting of solar irradiance and wind speed are analogous phenomena. Several variable factors are dependent on the metrological as well as environmental factors such as cloud formation, aerosol content, etc. But here assuming only the ambient temperature, humidity, and specific daytime as a training data set for further execution of data into mixed input-based cascades artificial neural network model. The time-series approach represents the estimation of electricity generation from the PV/wind generation system over a specific time slap. In the training stage, the DERs data set is transferred as the input values to $CANN_{MF}$ model. The number of input neurons was set at 10, single hidden layer (activation function used as LM-based backpropagation and number of neurons is set at 10). The linear activation function is employed, and 2 output layers are assigned with hyperbolic tangent sigmoid transfer function to get the best result of the $CANN_{MF}$ network. Before executing the proposed network, a different number of learning rates is assigned. There are 1000 epochs taken during the training period. At that duration, the $CANN_{MF}$ network is sufficiently trained. Once the proposed model is trained then data validation is performed for real-time short-term time DERs estimation series under variable metrological conditions. If applying the raw data set directly into the neural network, then there is a huge risk of simulated neurons reaches in saturation conditions. Therefore, to avoid this risk, firstly raw data must be normalized before applying to the $CANN_{MF}$ model, mathematically data normalization is represented by Eq. 15.

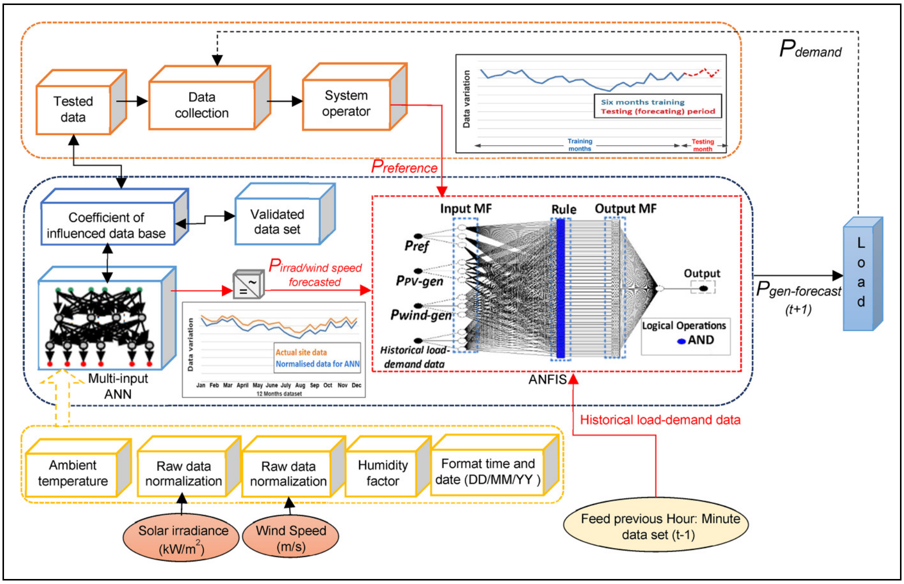

Figure 5. An external framework of ANN-based DERs forecast model and ANFIS for real-time power-demand management.

The second layer has two segments, the first one is the data learning that provides self-learning capability under different metrological input data and uncertainties of the generated power forecast followed by a regression plot. In the last layer, there is the feeding of the data set into a data storage unit and further use of this information in ISO units. This centralized processing unit is based on real-time demand predictive control scheme, which is capable of exactly mimicking the reference demand power values based on the corresponding load-demand variation. Typically, we use it to obtain the Euclidean distance of the vector equal to a certain predetermined value, through the transformation below, called min-max normalization:

$$X_n = \left[\frac{\{X - X_{min}\}}{\{X_{max} - X_{min}\}} + (U_l - L_l) + L_l \right] \tag{15}$$

Where X_n is normalized data range between [U_l:L_l]$\epsilon(-1, 1)$. X are the proposed data values, X_n are normalized data values. X_{max} and X_{max} are a maximum and minimum range of the real data respectively. U_l is upper range and L_l is a lower range of normalized data. The lower data range is referred to as the minimum irradiance and wind speed value.

Data collection and training approach

The ANN-based short-term forecast provides an effective analogous prediction phenomena as of the time series approach.[65] Here, training of irradiance and wind speed is carried out using the short-term ahead predicted value. For smooth and reliable power system operation, short-term forecasted data sets relied on several aspects such as load variation prediction, line status, power generation status, etc. The DERs information directly helps us in pre-planning and post-management of power demand against various uncertainty in grid systems. However, the designed forecasting model of wind speed is like solar irradiance forecasting due to almost similar environmental dependencies such as time of day, ambient temperature difference, cloud motion, humidity, etc. The Experimental Weather Prediction (EWP) is a physical system operator, which is implemented for efficient forecasting with respect to the time-series horizon over the desired test period. The EWP model is based on each hour time resolution, which realizes the forecasting of solar irradiance based on the spatial resolution for a specific data set. This approach provides precise prediction by system outcome up to the day ahead of time. In the EWP model, the satellite viewer function works based on the cloud images for predicting cloud movements and sky imagers are installed on the forecasting sites. So that it can be developed an efficient way of predicting the next month's data based on several meteorological factor variations. The variations in renewable energy resources also depend on several environmental factors such as time of the day, cloud formation, aerosol content, humidity, etc. These forecasted short-term data also depend on various variable factors such as time effects (atmospheric, seasonal changes, sudden contingency, storms, etc.). So, it is very difficult to forecast the DERs corresponding to the load variation. In this study, the $CANN_{MF}$ model was trained based on the solar irradiance, wind speed, wind direction and ambient temperature data set of proposed sites. The DERs forecast framework is considered the normalized data value during specific time series for an optimal fitting tool approach. The processing of input variables and training data sets is complex due to the inherent differences in respective time-series properties. In this case study, the optimal forecasting approach is evaluated, which is based on accuracy in the training algorithm. Here, the input data set are taken as the 6 months time series training data set and implemented in the MATLAB classifier tool. The time series characteristics followed by one/two hours before DERs data signify the short-term solar irradiance and wind speed ahead prediction. The case study is analyzed which is based on short-term actual data set from a specific site.[66] Training data has been taken from the Mahidad site (Gujrat, India) from January 2020 to June 2020 referred to in Table 4.

The practical real data set of the proposed site consists of 36730 samples for solar irradiance forecasting and 36730 samples for wind speed forecasting (historical data from 1 Jan 2020 to 31 July 2020) which is divided into the subsamples of training, validation, and testing. A simulation study is shown in Figure 6, the hourly average speed is 6.811 (*m/s*) recorded at the height of 81.82 meters in the proposed site. The data set for the month of June 2020 was used as the testing data set. The average pressure (979.8–1035.4*hPa*) and air density (1.2–1.4kg/m^3). For solar irradiance and wind speed forecasting, the input data set are taken as a 36730 × 1, which signifies the data normalization of each input variable. While the targeted data set is taken as 5510, which signifies the function fit for forecasting components. These 36730 samples were divided in such a manner that the training data set was taken as 25710 samples which are about 70% of the total data. On the other hand, the validation (15%) and testing (15%) data sets are taken as 5510 samples of the total data set, respectively. This data set of average wind speed (m/s) and solar irradiance (W/m^2) are in ST-based hourly format. Firstly, the maximum irradiance of this site is calculated, then further followed by data normalization, which limits the data within a range of 0 to 1. Thus, it will be preventing the saturation of neural network activation function.

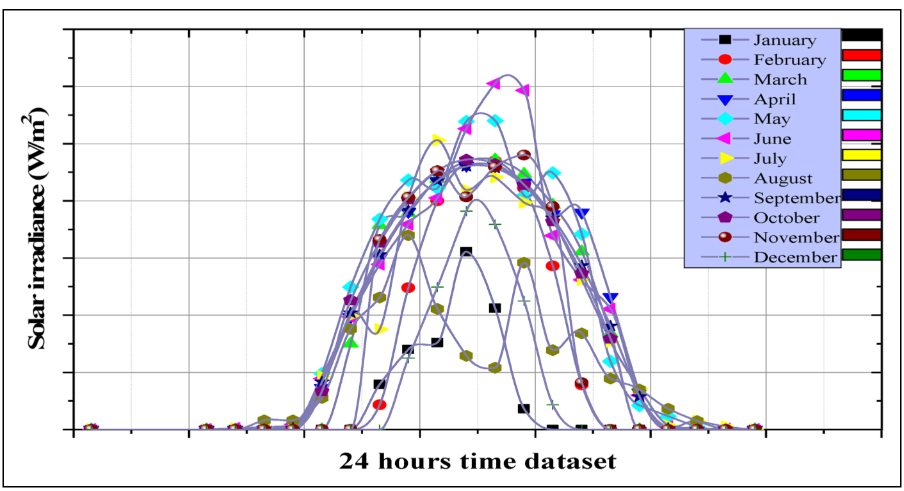

Figure 6. Executed irradiance data set (referred from Table 4).

Table 4. Demonstration of 12 h of data classification at mahidad, India, forecasting site.[66]

Time of the day (DD/MM/YYYY format)	Location ID: 9755 (Mahidad site, Gujrat, India)	Latitude: 23.5, Longitude: 72.63	Ambient level	Average pressure (979.8–1035.4hPa)	Reading recorded on 81.82 meter
Format (*Hour*: *Min* (1/1/2020)	GHI (W/m^2) before 1 h	GHI (W/m^2) before 2 h	Temperature (degree centigrade)	Wind speed before 1 h (m/s)	Wind speed before 2 h (m/s)
0:30	0	0	14.05249	6.8067 NW-SE	6.6739 NW-SE
1:30	0	0	13.23884	6.9997 NW-SE	6.8067 NW-SE
2:30	0	0	12.45883	7.1373 NW-SE	6.9997 NW-SE
3:30	0	0	11.76355	6.9876 NW-SE	7.1373 NW-SE
4:30	0	0	11.14835	6.6645 NW-SE	6.9876 NW-SE
5:30	0	0	6.599878	6.4108 NW-SE	6.6645 NW-SE
6:30	0	0	6.056253	6.0259 NW-SE	6.4108 NW-SE
7:30	13	0	6.603484	5.5812 NW-SE	6.0259 NW-SE
8:30	166	13	9.503256	5.8277 NW-SE	5.5812 NW-SE
9:30	361	166	13.69284	5.8422 NW-SE	5.8277 NW-SE
10:30	498	361	18.80711	5.8257 NW-SE	5.8422 NW-SE
11:30	617	498	22.65731	5.9129 NW-SE	5.8257 NW-SE
12:30	745	617	24.50366	6.1181 NW-SE	5.9129 NW-SE
13:30	846	745	25.32949	6.3760 NW-SE	6.1181 NW-SE

The yearly based normalized data sets are divided into daily possible mean irradiance and wind speed variation. A similar calculation can be employed for both wind speed and solar forecasting. A single algorithm is designed for both forecasting parameters because of analogous behavior. For the forecasting of GHI and its real-time data execution, all dependent parameters should be considered. These factors are dependent on cloud fraction (X_i) based on having a range of 0 to 1 and K_C using past data sets to get the cloud information [K_C^{Clr} for the clear sun (K_C) > 0.9) and K_C^{OCC} for occluding sun ($K \leq 0.9$)]. Where, Δt_i is forecasting based on the hourly period, now the forecasting of GHI for the clear sky is shown as Eq. 16.

$$GHI(t_0 + \Delta t_i) = [K_C^{Clr} + X_i(K_C^{OCC} - K_C^{Clr})] \times [GHI_h^{Clr}(t_0 + \Delta t_i)] \tag{16}$$

For the short-term prediction over a specific time (*hour: minutes*) for the individual day (*DD/MM/YYYY*). The DERs data set are taken as one hour before individual data of solar irradiance (W / m^2), wind speed (m / s), wind direction (in degree) and hourly ambient temperature. The wind speed prediction investigating by using the ANN to examine the various local atmospheric changes for all-time series horizons.

$$MAPE_{Wind\ speed} = \left[\sum_{i=1,2,.n}^{n} \frac{Wind\ Speed_{i(ANN)} - Wind\ Speed_{i(measured)}}{Wind\ Speed_{i(measured)}} \right] \times 100 \tag{17}$$

The accuracy of wind speed forecasting model is tested by MAPE is shown in Eq. 17. Here, $'n'$ is the input parameter for predicting the wind speed (using normalized data set on the forecast site), $Wind\ Speed_{i(ANN)}$ for ANN-based forecasting hourly model for a time span, $Wind\ Speed_{i(measured)}$ is based on forecasting of hourly DERs on a specified time span. This study demonstrated the training, testing and validation of the model on the proposed site.[66] Here the LM based $CANN_{MF}$ model is employed for short-term prediction of solar irradiance and wind speed forecasting in order to validate the system performance. Before executing the $CANN_{MF}$ model, network to be set learning capabilities, which is associated with various deep learning rates to get the least mean square error. Our proposed system provides optimal results by settling on fewer error values. In MLP model, the training algorithm is employed in Traingdx tool. There are many numbers of epochs employed to get the network adequately trained. Generally, LM based backpropagation technique was employed for the curve-fitting problem.[67] Here, the number of epochs was set as 1000. This methodology is prepared for estimating the solar irradiance as well as wind speed respectively under different environmental conditions. The fitting tool is comprised of the number of input neurons that was set at 10, in the hidden layer (Sigmoid activation function is employed and neurons are set as 10). While for a single output layer with activation function as linear transfer function for the best result of MLP, a number of output neurons were set as one.

Figure 7 shows the training state of $CANN_{MF}$, which is described by the failure iterations of validation and gradient. If several times validations fail occurs, that means that the dataset is overfitting during training data. For all epochs, the LM backpropagation algorithm is illustrated as 0.009156 on a log scale. This logarithmic-based value signifies the optimal local minimum position to achieve the goal function. The validation failure of iteration is signified by the increase of mean square error (MSE) in dataset validation.

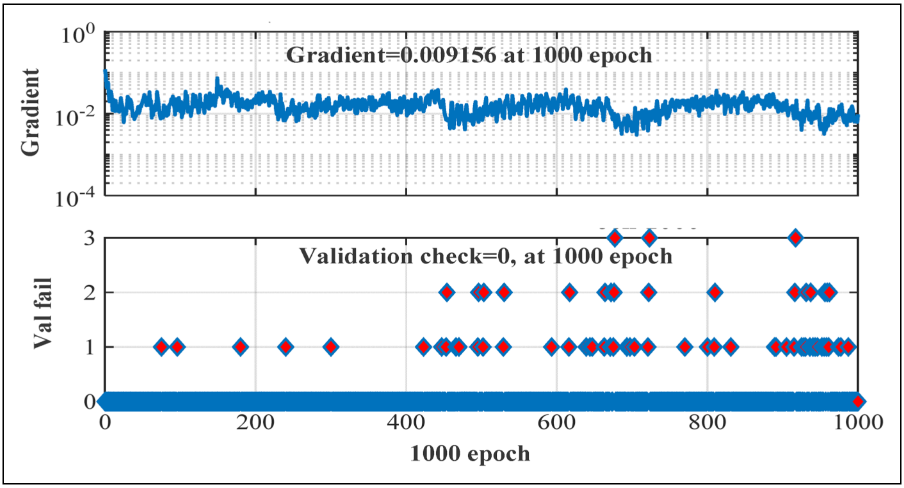

Figure 7. Training state of $CANN_{MF}$.

The output characteristics of solar-generated output power (P_{PVgen}) as per the average range of the solar irradiance 0–950 (W / m^2) using the proposed data set with ambient temperature variation. During the training period, it is observed that in the month of May-June the GHI level is higher at the proposed site. While P_{PVgen} is recorded as moderate level in months from August to November due to several metrological factors as well as low GHI levels, and variation in monsoon/rainy seasons. Therefore the P_{PVgen} is recorded as the lowest range in months from January to February due to extreme cold conditions as well as low GHI levels etc. on the proposed site. Thus, due to this solar PV panel temperature rise and the generated solar P_{PVgen} can be measured as in Eq. 18.

$$P_{PVgen}(t) = Clr(t).I_{SC}\left(1 + \frac{33}{1000}.cos\left(\frac{360d}{365}\right)\right)(sin\varphi.sin\delta + cos\varphi.cos\delta.cos(\omega t)) \quad (18)$$

The dynamic characteristics of the proposed intelligent based $CANN_{MF}$ the methodology is minimizing the power shortages that generally occur in real-time scenarios such as peak-time demand and lower generation period.

Where $'d'$ is represented as the random day, the decline angle of the sun is δ and the geographical latitude (φ) is considered for solar-generated power that is varying with respect to time ($P_{PVgen}(t)$). Here, I_{SC} is represented as solar constant and $Clr(t)$ is depicts a clearing index based on a different time scale. Hourly angle (ω) can be as $+15°/hour$ to as $-15°/hour$ determined by Eq. 18. Based on recorded data sets, simulation is carried out up to 31 days as depicted in Figure 8.

Simulation results

The proposed methodology used a very short-term series data set in,[66] which is implemented in the MATLAB fitting toolbox. The normalized irradiance amplitude is being

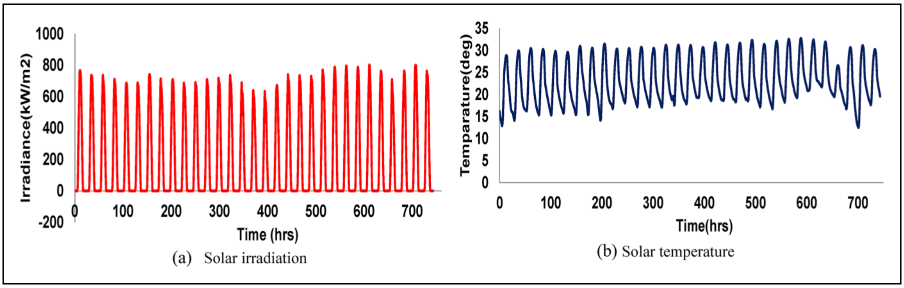

Figure 8. Simulation characteristics of data considered in the proposed location for the solar irradiance prediction. (a) Solar irradiation. (b) Solar temperature.

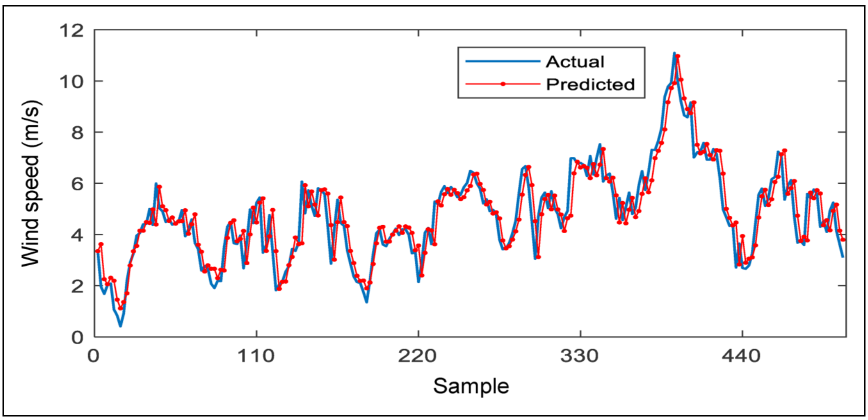

Figure 9. Validation of actual wind speed vs forecasted $CANN_{MF}$ based on wind speed hourly values (on July 10, 2020).

measured as [0–1000] kW / m^2 with respect to each time slap over one month period. The maximum measured PV power is followed by an observed irradiance level under 0–1000 kW / m^2. Figure 8 shows that $CANN_{MF}$ based solar irradiation forecast, which is approximately same as the actual irradiance variation. The results are utilized for long-term GHI forecasting under highly variable environmental conditions.

Normalized input data set is taken for training to forecasting wind speed (m / s). While the targeted data taken as 5510 × 1 signifies the function fit for forecasting components. The 3400 samples are divided in such a manner that the training data set is taken as 2400 samples of total data. On the other hand, the validation and testing data set taking as 550 samples of the total data set, respectively. $CANN_{MF}$ based model is testing for a month, 10 July 2020.[66] Figure 9 shows that the predicted wind speed characteristic under range of 0–12, which is approximately same as the actual wind speed variation. Further, the designed ANFIS model is based on the variation in various observational data and forecasted data from the proposed hybrid renewable energy system. The proposed model includes two DERs inputs and MFs includes based on three input parameters. The FIS controller is assigned for maintains the constant load level with utilization of maximum demand by minimizing the ΔP_{demand} deviation. The forecasting approach is employed for fluctuating load demand as referred in Figure 10.

To validate the forecasted data set, the implementation of the proposed methodology is analyzed on a fluctuating load site. Thus, the real-time data set of renewable energy resources was implemented from the Mahidad site in Gujrat state, India.[66] While the load-demand management is carried out by the ANFIS-based model in the proposed site. To study the model performance based on seasonal variations, our proposed case study is a demonstration of one-hour-ahead load forecasted demand for the summer season (in the second week of July) of the year 2020. the input data is taken as a time series graph for the load variation with respect to demand. From Figure 11, the maximum load was observed as $1035e + 2\ kW$ on 13 July 2020 (Monday). On the other hand, estimation of total real demand is based on time-varying load. Usually, it is a complex task for an independent power system operator. Here, the real-time information of the estimated power demand is

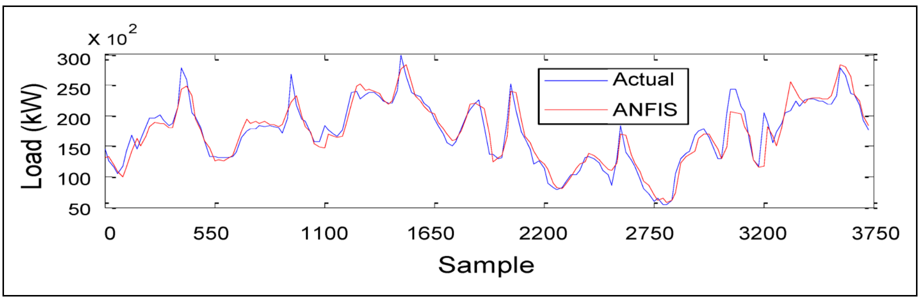

Figure 10. Load power forecasted variation with respect to actual values.

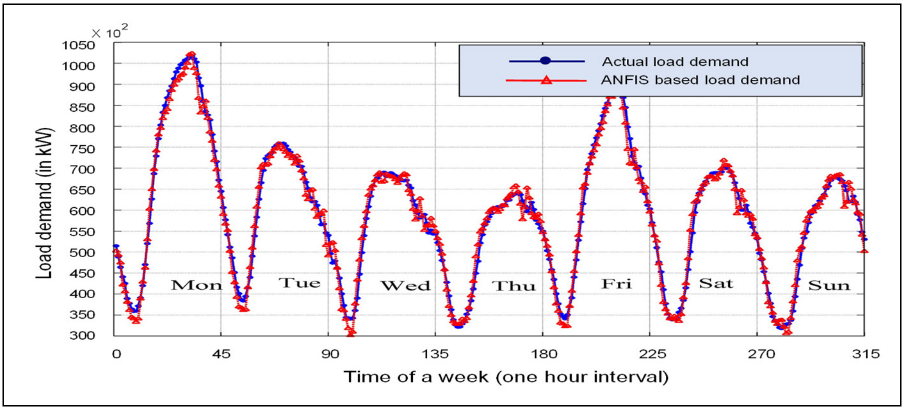

Figure 11. Average weekly power response results from 13 to 19 July 2020 data set.

advantageous information for various power generation companies (GENCOs) for real-time demand scheduling and control.

In the proposed site, the maximum residential load-demand is approximately $1030e + 2\ kW$, so the forecasted value can be fed to the real-time system which is worked for the ISO demand management system. Also, from demand power characteristics there is continuous fluctuation in the demand site because areas have large load variations in the industries. The proposed hybrid neuro-fuzzy-based model was successfully employed for forecasting and further management of the load demand. Thus, the ANFIS-based methodology provides optimal power response prediction, which is based on weekly forecasted results, we can design the model for the optimal scheduling for a specific time slap.

Error evaluation and performance analysis

The real-time forecasting analysis is significant for the load-demand validation at regular instants. The error must be checked continuously at regular intervals until the training mechanisms stop. Usually, the maximum learning rate of the ANN model is in between the ranges of 0 to 10. If variation occurs in weight functions, then the learning rate appears as a quantifier followed by data acceleration. If the learning rate depicts the low forecasted value that means changes occurring in the weight vector so that one epoch changes to the next epoch. If the learning rate specifies a high value that means it is undesirable to the network, which may lead to the risk of overshooting.[68] Thus, the proposed ANN network is associated with a slow learning rate that takes more operational time. Figure 12 describes the error histogram plot during the training process. Here, the overall error ranges of the $CANN_{MF}$ network are ranging from -0.95 to $+0.95$ for 20 bins and every bin matches to a width of 0.093465. Moreover, these bins are characterized as numerous samples, each one is having an error of the validation data.

Here, the LM-based ANN model plot provides the overall optimal prediction. Also, a similar algorithm is designed for short-term solar irradiance as well as wind speed as

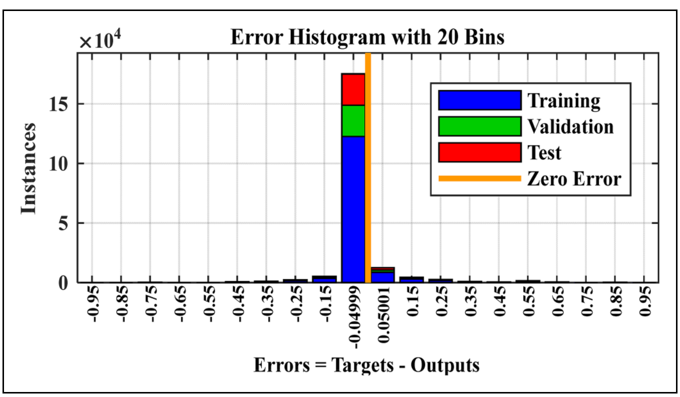

Figure 12. Error histogram of $CANN_{MF}$ based forecasted model.

input variables.[66] Since, the forecasted plot of short-term solar irradiance is analogous to short-term wind speed forecasting, which is based on environmental variation and dynamic nature. In the case of extreme penetration of metrological factors (cloud level, aerosol content, etc.) in which the characteristic of short-term irradiance and wind speed is predicted. From Figure 13, the best validation performance is at 992 epochs for the effective operation of forecasted systems. The $CANN_{MF}$ based classifier learner is trained for the 1000 epochs to get the optimal short term forecasting results with LM during performance evaluation.

Figure 13 shows the best validation performance plot of the trained datasets for further testing as well as validating the proposed system performance. Here, it is depicted that when the epochs are increasing, then the error (e) values keep on decreasing. But at 992 epochs, the value of $'e'$ rises as the CNN overfits the training dataset during the validation of the normalized dataset. So, to avoid this issue, the time series is regulated to stop the training just after the five successive validation check fails. Therefore, the optimal performance is revealed by obtaining the epoch at minimum validation check fail. The LM Based ANN model was employed for the short-term prediction of solar irradiance and wind speed. Our proposed methodology is a dynamic approach that has better reliabilities and accuracy for the prediction of short-term DERs variables. After getting a significant amount of mean square error within the specified limit. The proposed system implies a high degree of accuracy.

In this study two dependent variables (V_1 for the GHI and V_2 for the ambient temperature) has been taken, which is based on the cause-and-effect relationship. Similarly for the wind forecasting variables such as wind speed V_3 and wind direction V_4. Thus, the resulting linear regression equation in between these variables V_1, V_2, V_3 and V_4. Here, the normalization of regression (R) plot is representing the interrelation between two dependent and their correlated variables. Thus, each forecast variable is associated with another

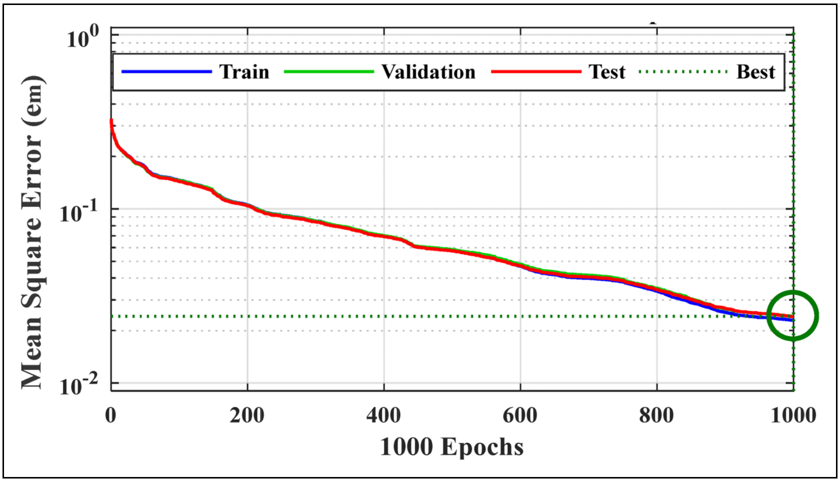

Figure 13. Best validation performance of $CANN_{MF}$ is 0.024105 at 992 epochs.

correlated variable then it gives the overall regression within the specified range. Usually, there are three types of regression plots based on the spectrum such as simple, linear, and multiple regression. Here proposed study utilizes a linear regression (plotting the linear regression line between two dependent variables). The results show that the ANN regression model effectively forecasts solar irradiance and wind speed on an hourly basis. So, this research proposed LM-based cross-validation as the enhanced ANN technique for forecasting in resilient energy systems. However, the validated response of DERs with optimal values are shown in Figure 13, which are obtained with respect to the actual values.

Here, the value of R^2 is nearly to equal or less than 1, which depicts the accuracy of the proposed ANN model in order to fits the training and testing datasets. Thus, the prediction of DERs variables is close to the actual data set of sites. In Figure 14, the regression is 0.9087 during training time, while regression is 0.92238 during the validation period, and during testing, regression is 0.90728. Thus, during all phases value of R is 0.91772 which is near to 1.

Table 5 shows the range of regression values in all these three phases (training, testing, and validation). So, the value of R is within 1. The forecasting accuracy was estimated by computing the MSE between the actual and forecast values. The MSE and RMSE of the proposed methodology using ANN as well as ANFIS-based real-time model that can accomplish better prediction with minimum error. Furthermore, this proposed intelligent-based hybrid renewable energy system implements the extension of these Simulink results, which are obtained from real-time operational and performance analysis. To evaluate the forecasting efficiency of the proposed ANN model, similar features of the input data set is used for training purpose with the MLP model MATLAB Simulink tool. From Table 5, the forecasting results are depicted that the designed $CANN_{MF}$ the model has much better efficiency than other models.

As concluded in Table 6, the designed $CANN_{MF}$ based DERs forecasting results are trained with the 6-month hourly dataset in an efficient manner. Further, these forecasted

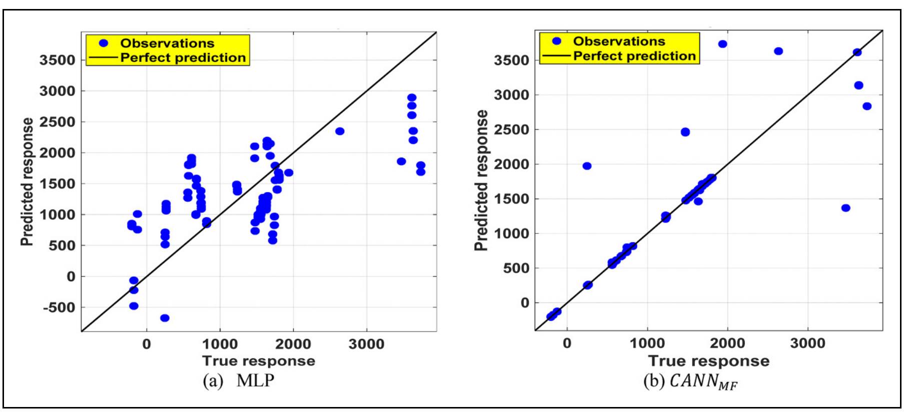

Figure 14. Plot fitting of regression plot for 36730 recorded samples (183 solar days). (a) MLP. (b) $CANN_{MF}$.

Table 5. Error analysis of proposed forecasted system.

Forecasted Parameters		$CANN_{MF}$ MSE (e_m)	$CANN_{MF}$ Regression	ANFIS Cross entropy
6 months training		5.63	0.9373	2.43
Validation		5.69	0.9323	4.30
Short term testing on random time slap		6.22	0.90728	3.68
Testing at proposed site	Monthly basis	3.11	0.91746	-
	Hourly basis	2.48	0.93246	1.08

Table 6. Quantitative analysis of the proposed system with another intelligent technique.

Parameters Model type	Specification $CANN_{MF}$	Specification MLP
Network structure	LM based cross-validation	Conjugate gradient-based
Total training samples	25710 samples	25710 samples
Performance evaluation criteria	mean square error (e_m) for hourly-based data	mean square error (e_m) for monthly based data
System accuracy	98.2%	89.60%
Training duration	17.10s	26.808s
forecasting time	18ms	31.05ms

data are utilized in the ANFIS model for a real-time power demand management system. It also confirmed that during testing and validation, the forecasting means error and cross-entropy are less than 5% under a specific slap of the day at the proposed site.

Conclusions

The ANFIS model demonstrated a better approach for the effective utilization of hybrid renewable energy resources with an enhanced forecasting accuracy. The testing results of the mean error and cross-entropy is less than 5% under a specific slap of the day at the proposed site. The proposed real-time power demand management approach has been optimally designed by the ANN-based DERs forecast model for optimally utilizing the solar and wind-generated power under different environmental variations. Also, the proposed methodology shows that $CANN_{MF}$ model accomplished better prediction with minimum error. While the structure of the proposed $CANN_{MF}$ the network is much larger than the MLP model, which mimics the correlated structure of multiple-layer ANN. Thus, in the stochastic power system, an optimistic method is required to maintain the power demand-load balance in a real-time power management system. This adaptive model can be further modified using a fuzzy Q learning approach with a support vector regression-based hybrid algorithm. Our intelligent-based proposed hybrid renewable energy system can be utilized when continuous electric power is deficient was a major limitation. Alternatively proposed approach is a dependable solution in rural as well as semi-urban areas.

Future work will be developed optimal control strategies with the consideration of several input metrological parameters such as aerosol content, humidity, and air density for the feasible operation of resilient energy systems. The future study will be comprising the real-time hardware setup with the existing one and testing on the multi-microgrid system. The simulation results can also be incorporated with time horizon forecasting under several environmental factors such as peak demand periods of the day, cloud formation, aerosol content, etc. in order to achieve the real-time long-term forecast Here, the real-time power management system is implemented in a multi-agent-based independent system controller that regulated several aspects of grid parameters to resolve the peak demand imbalance issue.

Nomenclature

Indices and parameters

δ	*Decline angle of the sun*
K_C^{Clr}	*Cloud information for the clear sun (Kc > 0.9)*
K_C	*To get the cloud information*
K_C^{OCC}	*Cloud Information for occluding sun (K≤0.9)*
ΔP_{load}	*Fluctuations in load*
ΔP_{demand}	*Variation in demand*
$\widehat{y_m}$	*Forecasted values*
φ	*Geographical latitude*
y_m	*Measured values*
P	*Forecasted point (individual)*
Q	*Forecasting points (total)*
w_{ij}	*Weight functions*

Acronyms and abbreviations

ARMA	*Autoregressive moving average model*
ANFIS	*Adaptive neuro-fuzzy inference system*
CFANN	*Cascaded forward artificial neural network*
C_{Coef}	*Correlation coefficient*
DERs	*Distribution energy resources*
EWP	*Experimental weather prediction*
FIS	*Fuzzy inference systems*
FFANN	*Feed-Forward artificial-neural network*
GENCOs	*Generation electricity companies*
GHI	*Global horizontal irradiance*
LTLF	*Long-term load forecast*
MAPE	*Mean absolute percentage error*
NWP	*Numerical weather prediction*

PSO	*Particle swarm optimization*
RMSE	*Root mean square error*
SVM	*Support vector machine*
U / VSTLF	*Ultra/Very short-term load forecast*

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