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A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings

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ABSTRACT

Electrical load forecasting plays a vital role in order to achieve the concept of next generation power system such as smart grid, efficient energy management and better power system planning. As a result, high forecast accuracy is required for multiple time horizons that are associated with regulation, dispatching, scheduling and unit commitment of power grid. Artificial Intelligence (AI) based techniques are being developed and deployed worldwide in on Varity of applications, because of its superior capability to handle the complex input and output relationship. This paper provides the comprehensive and systematic literature review of Artificial Intelligence based short term load forecasting techniques. The major objective of this study is to review, identify, evaluate and analyze the performance of Artificial Intelligence (AI) based load forecast models and research gaps. The accuracy of ANN based forecast model is found to be dependent on number of parameters such as forecast model architecture, input combination, activation functions and training algorithm of the network and other exogenous variables affecting on forecast model inputs. Published literature presented in this paper show the potential of AI techniques for effective load forecasting in order to achieve the concept of smart grid and buildings.

Contents

Abbreviations: AI, Artificial Intelligence; ANN, Artificial neural network; AR, Auto-Regressive; ARIMA, Auto-Regressive Integrated Moving Average; ARMA, Auto-Regressive Moving Average; DR, Demand Response; DG, Distributed Generation; SG, Smart Grid; SB, Smart Building; HS, Hybrid System; GA, Genetic Algorithm; ES, Expert System; TS, Time Series; SVM, Support Vector Machine; AIS, Artificial Immune System; WNN, Wavelet Neural Network; BP, Backpropagation; LM, Levenberg–Marquardt; ISO, Independent System Operator; MAE, Mean Absolute Error; RMSE, Root Mean Square Error; MAPE, Mean Absolute Percent Error; MLP, Multi-Layer Perceptron; MR, MADALINE adaptation Rule; R, Correlation Coefficient

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Introduction to electrical load forecasting and its applications

Load forecasting is future load prediction, which plays a very important role in the energy management system and better planning for the power system. In the procedding years, a large number of researches have been published on accurate short term load forecasting (STLF) due to its impact on the reliable operation of power systems and economy. It ensures the reliable operation of power system that leads to uninterruptable power supply to the consumer [1]. The operations of power system, for example scheduling, maintenance, adjustment of tariff rates and contract evaluation can be conveniently carried out by accurate load forecast [2]. Energy policy making decision can be carried out based on accurate load forecast. Sevral decisions of power management system can be carried out on the basis of accurate load forecasting such as power system operation, maintenance and planning [3]. Effective planning of power systems can save millions of dollars, which plays a significant role in the economic growth of a country.

There is a strong impact of weather variables on load demand such as temperature, relative humidity, dew point, dry bulb temperature, wind speed, cloud cover and the human body index. The multiple load consumed by individuals also creates enormous impact on load forecasting. However, in order to achieve the higher forecast results, there is need to accommodate all factors affecting on load demand as forecast model inputs such as; historical load and respective weather data. In this modern era of technology, an accurate load forecast plays a vital role to implement the concept of smart grids and smart buildings [4].

1.1. Classification of load forecasting

Load forecasting is divided into three categories by most of researchers but some of them divided it into four categories [5]. Normally Load forecasting can be divided in three categories on the basis time interval.

- Long term load forecast(1 year to 10 year ahead).
- Medium term load forecast (1 month to 1 year ahead).
- Short term load forecast (1 h to 1 day or 1 week ahead).

Long term load forecast is used for the long term power system planning according to the future energy demand and energy policy of the state. Medium term load forecast is being used for the efficient operation and maintenance of the power system. Literature shows that, mainly efforts are concentrated on short term load forecasting in preceding years. It is due to the importance of short term load forecasting and it also play a vital role in optimum unit commitment, control of spinning reserve, evaluation of sales/purchase contracts between various companies.

1.2. Short term load forecasting (STLF) and its importance

Literature review shows that, a large number of researches have been published on short term load forecasting for different load scenarios. Fig. 1 illustrates that, the types of load forecast and its application of short term load forecast for reliable and efficient energy management system. Fig. 1 also depicts that, seasonal load forecast scenario as STLF case studies to analyze the performance of forecast model and utility perception for multiple consumers.

The major objectives of accurate STLF are given below:

- Generation scheduling of power system.
- Secure and reliable operation of power plants.
- Economic dispatch and reliability.

Generation scheduling can be carried out with help of accurate load forecast to determine the allocation of generation resources, operational limitations, environmental and equipment usage constraints. For hydropower generation units, optimal release of water reservoir and generation scheduling of power house can be carried out on the basis of STLF. For thermal power plants, load forecasting can be utilized to determine the unit commitment function for minimum production cost.

Another application of STLF is to ensure the power system security. The accurate load prediction is an essential tool to determine the optimal operational state of power system. Furthermore, this information can also be utilized to prepare the power system in accordance with future load state and corrective actions.

Another important application of STLF is economic dispatch and reliability of power system. The reliability of power system highly fluctuates with the abrupt variations of load demand. For example, if the load demand is underestimated then system may face the shortage of power supply. Therefore, it is difficult to manage the overload conditions and overall power system quality. Conversely, if the load demand is overestimated then a lot of available resources would have been spent to generate the overestimated power demand. In such kind of circumstances, the precision of load has gained tremendous popularity in the last decade [6].

1.3. Characteristics of load curve

In order to design a good forecast model, the load data should be closely analyzed and dynamics should be clearly understood. Based on the behavior and variation in load data, the necessary operations should be performed on load data to acquire the good forecast results. Data pre-processing or data normalization is one of the data treatment methods, which can be applied on the basis load profile analysis. Input data of the network can be classified into different clusters based on their characteristics, which may increase the network performance.

Fig. 2 shows the graph of input load demand (MW) of six years (2004–09) ISO New England grid. The load trend can be analyzed with load demand graph and this type of analysis can be useful for energy policy making decision [9]. Seasonality trend can be easily observed in load profile of ISO-new England grid data as load pattern repeats according to season of year. As the load demand in summer season is about double than the winter season. This large deviation in load demand is a result of variation in metrological conditions.

One year load demand data (MW) of the ISO New England grid is shown in Fig. 3. It highlights the load profile of peak and low load demand. This analysis is helpful in power system planning and scheduling. In Asian countries the load demand is very high in summer due to an increase in the temperature and relatively low in the winter season.

The load demand of the consumers is varied in cyclic manner during the 24 h of a day. It is due to consumers daily and routine activates, which depend on the time the day such as working hours, school hours and nighttime. Consequently, the load demand for a power utility is varying over the whole day.

Fig. 4 shows the load demand of a one week from Monday to Sunday that is varying with every hour of the week. It can be observed that, the pattern of load demand is repeating throughout the week with variation of peak load demand. The load demand gradually decreases in the night time and it becomes minimum load consumption during the morning time. However, the load demand starts increasing with passage of daytime because the people's activities start gradually. The load demand again starts decreasing after mid night as human activities are reduced. The load demand also varies in different days of week due to different social activities of the peoples, which causes the load variation.

Fig. 5 depicts the loads demand of one complete month (30 days). It depicts that, in working days the load demand is much higher than the off days (Saturday and Sunday) due to increase in social activities. This weekly pattern is repeated more or less throughout the month as shown in Fig. 5.

1.4. Co-relation analysis between weather variables and load data

From the literature review is can be observed that, there is strong correlation between weather variables and load demand [7]. Generally, load demand of power is increases in summer season due to raise in temperature and lower in winter season. So, weather variable must be included as forecast model input in order to achieve acceptable forecast accuracy. The graphs in Figs. 6 and 7 represent the relationship between the dew point and dry blub temperature with load demand. The graph shows that as the value of the dew point increases, the power system demand also increases and vice versa. The human

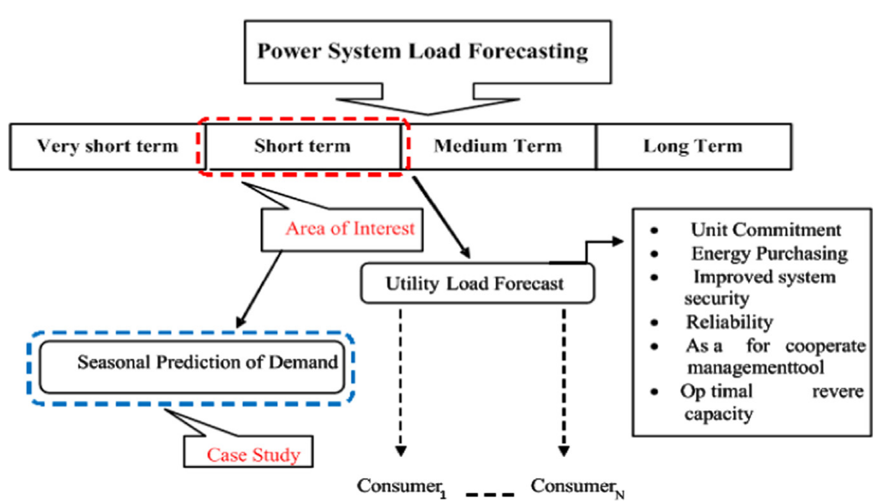

Fig. 1. Types of load forecasting and application of STLF.

perception study shows that the dew point in the range of 40 F to 60 F is suitable for humans. The load demand is low within this range of dew point.

Dry blub graph shows that, the load demand is relatively low in the range 45 F to 60 F. If the relative humidity is 100%, then the load patterns of dew point and dry blub becomes similar. From this graph, the effect of dew point and dry blub can be analyzed. However in order to achieve the better forecasting results, dew point and dry blub information must be included as forecast model input.

1.5. Pre-processing of data

Pre-processing of input data is a transformation process of data in normalized form. So, that the network can easily learn the patterns and generate a better output results. In standard normalization process, each input data point transform between interval 0 and 1. The data of each input can be normalized separately or in groups of input variables. The normalization process may enhance the learning process of network and consequently, ANN based forecast model will generate better forecast results [8].

Data normalization can be performed using the following formulas:

$$Normalized\_load = \frac{\overline{X} - X_{min}}{X_{max} - X_{min}} \tag{1}$$

$$Normalized\_load = \frac{\overline{X}}{X_{sum}} \tag{2}$$

$$Normalized\_load = \frac{\overline{X}}{X_{max}} \tag{3}$$

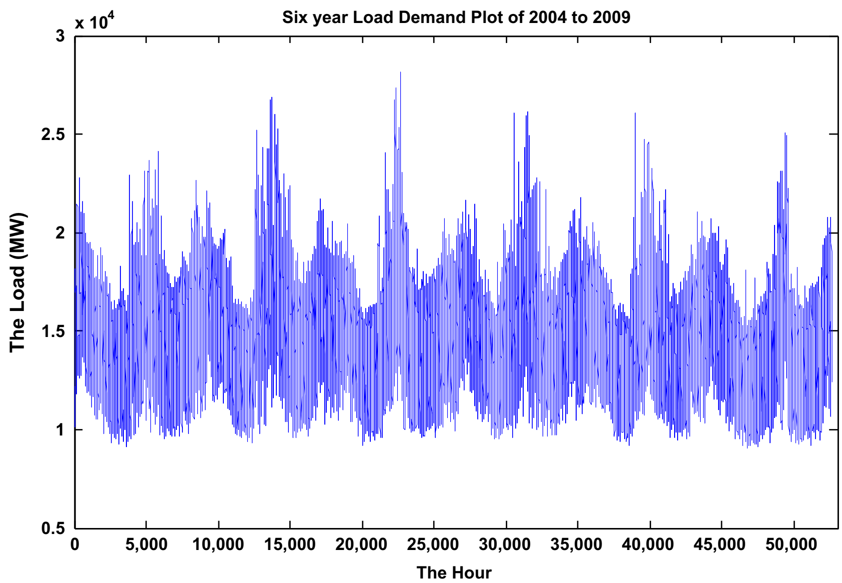

Fig. 2. Six year (2004–09) load profile of ISO-New England grid.

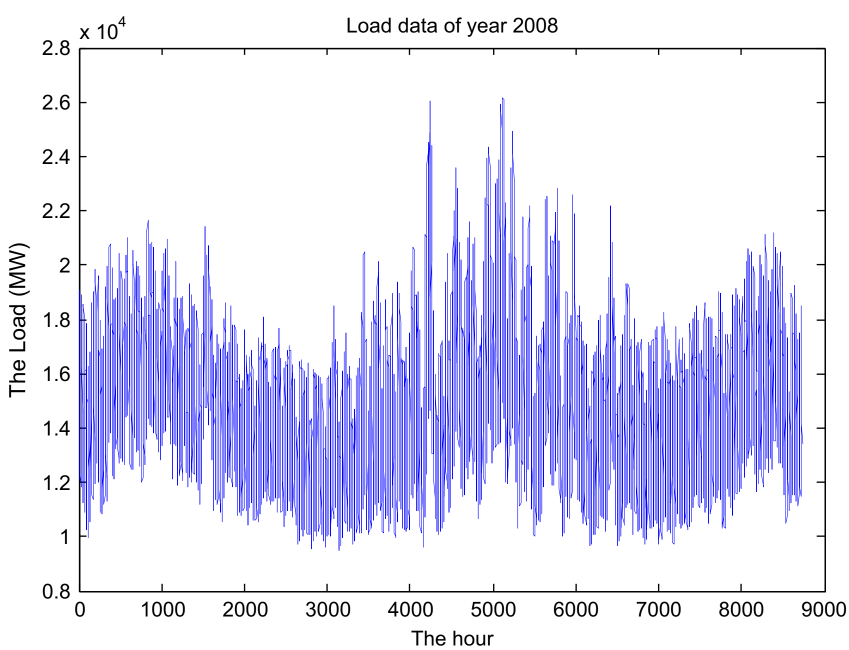

Fig. 3. One year 24 hourly load Profile of year 2008.

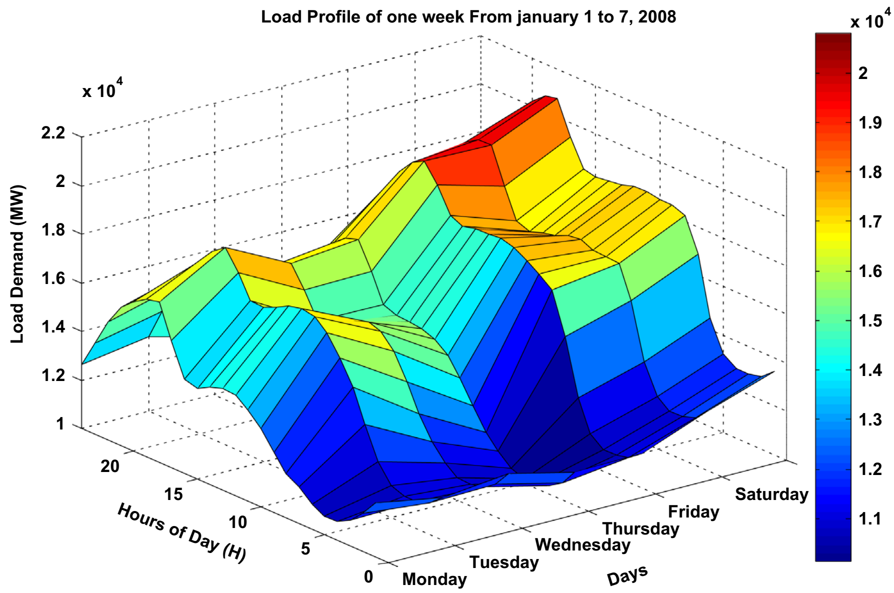

Fig. 4. Load profile of January 1 to 7, 2008.

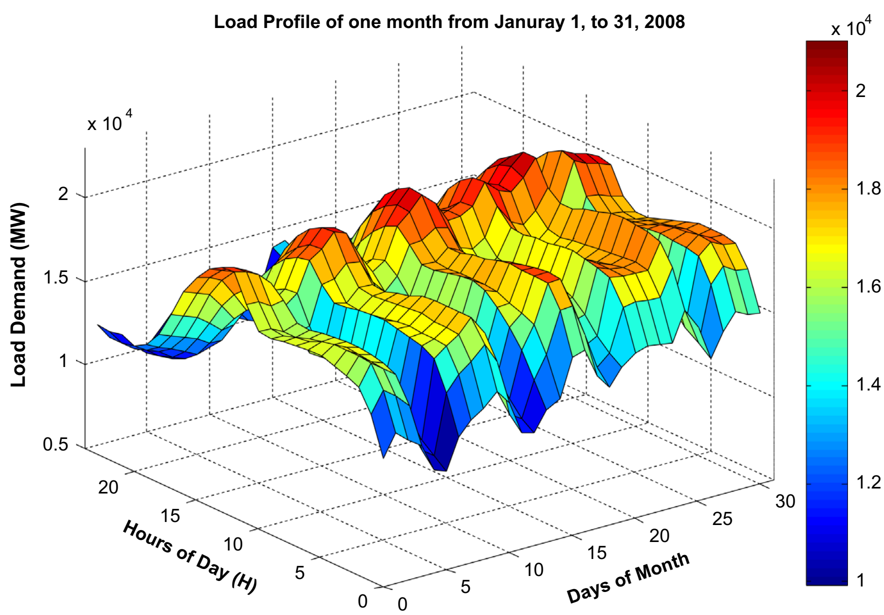

Fig. 5. Load profile of ISO New England grid of January.

$$Normalized\_load = \frac{\overline{X} - X_{avg}}{X_{max} - X_{avg}} \quad (4)$$

where

- $\overline{X}$represents the actual value of load.
- X max represents the maximum value of load.
- X min represents the minimum value of load.
- $Xsum$ represents the sum of all load values.
- $Xavg$ represents the average value of load.

1.6. Selection of forecast model inputs

Load forecast accuracy greatly depends upon the better input selection of neural networks. Moreover, most influential and highly correlated input patterns may give better forecast results. However, there is no general rule defined for input selection of

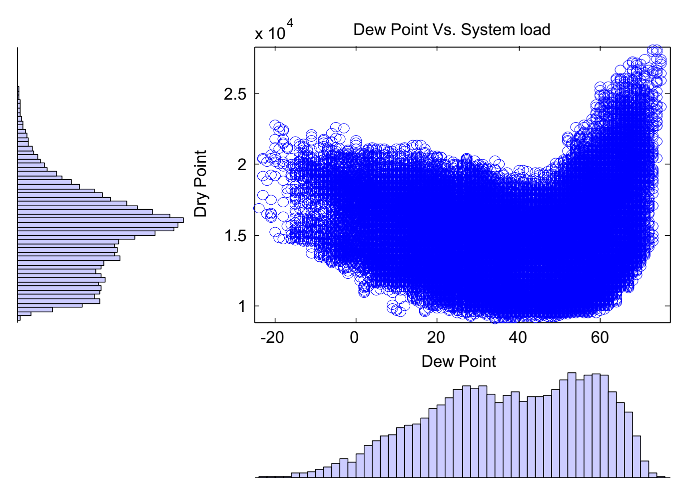

Fig. 6. Relationship between dew point and power load demand.

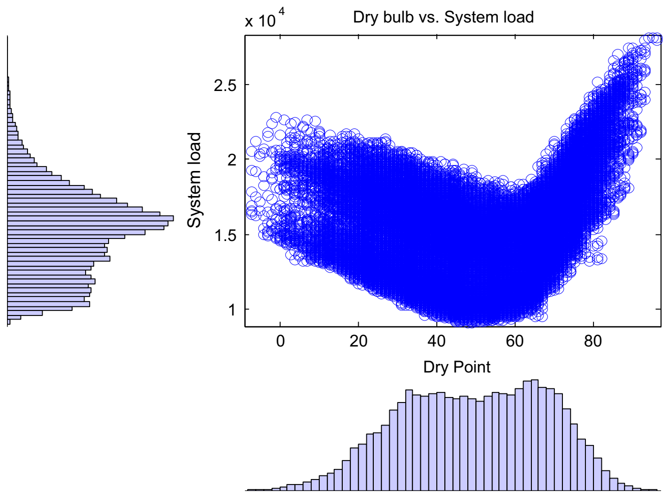

Fig. 7. Relationship between dry blub and power load demand.

forecast model. An appropriate input selection can be carried out based on engineering expertise or technical experience [9]. Some statistical and correlation analyses can be very helpful to determine the inputs, which significantly increase the load forecasting accuracy.

The input data of NN based forecast model can be divided in two types: training data and testing data. Training data is used to train the network and testing data is utilized to measure the performance of forecast model. Four year 2005 to 2008 hourly load and weather data of New-ISO England grid is used to train the neural network [10]. Load data of 2009 year is used to test and measure the accuracy of the forecast model. Type and number of Inputs of forecast model is very important to enhance the forecast model performance. There are no specific defined rules for input selection of forecast model but suitable selection can be carried out based on the field experience and expertise [9].

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The correlation analysis is used to analyze the relationship between weather variables, historical load data and calendar events on load demand. Highly correlated historical load data, weather variables and other influencing time related variable are consider as forecast model inputs in order to enhance the performance of forecast model. Moreover, several case studies are designed with different combination of forecast model inputs to analyze and enhance the performance of model. However, the best combination of historical load data, respective weather parameters and other exogenous variable such as day of the week, type of day are selected as forecast model inputs.

The proposed forecast model inputs of ANN model are shown in Fig. 8.

1.6.1. Previous correlated load data

Where L_d (w, d, h) represents the load demand of a particular hour of the same day and week.

- L_d $(w, d, h{-}1)$: represents the load demand for pervious hour of the same day and week.
- L_d $(w, d{-}1, h)$: represents the load demand for same hour of the week in previous day.
- L_d $(w{-}1,d,h)$: represents the load demand for same hour of a day of the previous week.

Load inputs of the previous hour, day and week are highly correlated.

1.6.2. Working day or off day

The type of day refers to either a working day or an off day (weekends or special occasion). On or off days the load demand is quite different from the normal day due to the changes in human activities. In weekends, the load demand is lesser than working days because the office buildings, factories, and other working places are closed. It is observed that, people may also get up late in the morning during weekends than the working days, which also shift the peak load demand. UK grid load profile shows that, the load demand of working and weekend days (Saturday and Sunday) may also differ. It is because of change in human activities such as some of families prefer to buy the house items or family gatherings on Sunday.

During the working days, the load consumption is usually higher than off days as factories, offices, and other working places will again start their production. Therefore, the load demand pattern of working days and weekends are different. The local customs and traditions of certain locality may also affect the load pattern.

1.6.3. Day pointer D(k) and hour pointer H(k)

$D(k)$ and $H(k)$ are the day and hour pointer respectively, which are used to identify the load demand at particular hour and day. From the daily load profile analysis, it can be clearly observed that, the load demand is varies in 24 h of a day. As discussed before, the load demand of the consumer start increasing as the day time goes up. Moreover, it also can be observed that, load demand is quite different in weekdays than the weekends. So, that in order to enhance the performance of proposed forecast model, these inputs day of week (Monday is the first day and Sunday is the seventh day of the week) and the hour of the day are also included as model input.

1.6.4. Weather inputs

The load demand of the consumer is greatly influenced by the metrological factors such as: dry blub and dew point. Literature review shows that, there is strong correlation between the metrological condition and load demand, especially temperature, dry blub and dew point [11].

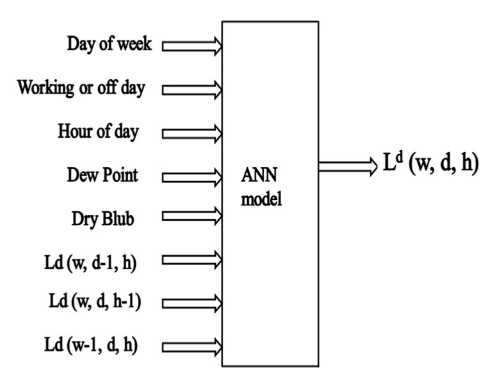


Fig. 8. ANN forecast model inputs for STLF.

1.7. Load forecasting techniques and classification

In the last few years, extensive research is going on future generation power system called smart grids to fulfill the needs of demand response mechanism, which can be implemented with accurate load forecasting. There are several techniques for short term load forecasting but mainly these techniques can be divided into two categories as discussed below [12].

- Parametric techniques (statistical techniques).
- Non-parametric techniques (artificial intelligence techniques).

Fig. 9 depicts the classification of short term load forecasting (STLF) techniques. Moreover, it is also represents the several hybrid techniques with artificial neural network for short term load forecasting and critical analysis of previously implemented techniques in order to achieve higher forecast results.

1.7.1. Statistical and time series based forecasting techniques

Statistical method includes time series technique [13], linear regression [14], autoregressive moving average [15], general exponential technique [16] and stochastic time series [17]. The statistical technique gives less prediction error if the input behavior under normal conditions. If there is an abrupt change in environmental or sociological variables e.g. changes of the weather, type of the day, a large forecasting error can be observed. This is a major drawback of statistical techniques [12].

1.7.2. Artificial intelligence based forecast techniques

The ANN received great attention by the researcher since mid 1980 for load forecasting problem and attracts the researcher as a powerful computational tool for the prediction problems. The ANN provides much better performance as compared to previous implemented techniques for non-linear input variables. The neural network has ability to solve the complex relationship, adaptive control, decision making under uncertainty and prediction patterns [18].

The ANN has more advantages than statistical model, as it has ability of map the input and output relationship without making complex dependency among the inputs. The ANN extracts the nonlinear relationship between input variables using training process of network. The network can learn the future output behavior of load demand by using pattern reorganization function. However, the output patterns have been learned by applying the input training data patterns to train the network. Appropriate learning algorithm, suitable training data and optimized network structure may increase the overall performance of network and reduce the complexity [19]. Moreover, primary steps ANN based load forecast model are provided in Fig. 10.

1.8. Significance of ANN approach

The ANN shows superior performance than the statistical techniques, because ANN has better capability to map the inputs of model to outputs without making complex mathematical formulations [20]. ANN model extract the non linear relationship between among the model inputs by different network learning mechanisms using training data. Unlike the expert system, ANN does not rely on human expertise and shows more robust behavior under different uncertain input scenarios.

ANN techniques show better performance than statistical and time series methods for forecasting problem by dynamically the changing interconnected weight values. However, high correlation impact and pre processed of training data, optimal network structure and better learning algorithm of neural network may enhance the performance of network. In addition, it also gives fast convergence speed of network, low computational complexity, reduced the training period and better generalization [21]. There

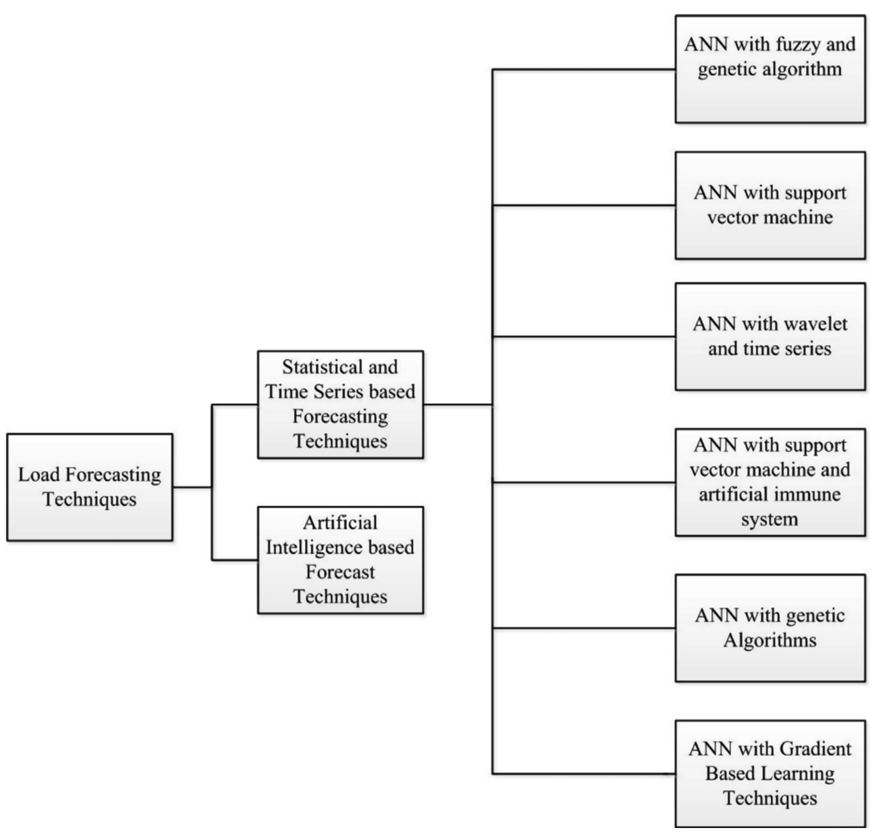


Fig. 9. Classification of short term load forecasting techniques.

some studies was conducted as application of Artificial neural network based model for smart grid as given in Table 1.

1.9. Introduction to artificial neural network

In 1942, McCulloh and Pitts performed an experiment to model the bio-systems using nets of simple logical operation for simple nonlinear model of real neuron. This experiment opens a new horizon in the field of computational calculation. Moreover, Table 2 summarizes the developments of artificial neural networks (ANN) from early stages.

In the last decade, the artificial neural networks (ANN) get much attention by the researcher and consider as a powerful computational tool for complex problems. The ANN also have a mimic ability like a human brain's to make decision and shows adaptive behavior for complex, noisy set information.

ANN models attempt to achieve the best performance through densely interconnected small processing units of the network is called neurons. The network of artificially interconnected neurons explores multiple competing hypotheses by simultaneously massive processing for the better results. ANN based models have been successfully implemented in several fields of daily life such as; Biomedical applications, aerospace, automotive industry, electronics and finance industry etc [30].

1.10. Biological neuron

In the last few decades, the studies have shed light on the human brain and nervous system construction and operation [41]. The basic unit of human nervous system is neuron. Central body, dendrites, synapses and an axon are the major components of a neuron as shown in Fig. 11.

The information signal flow in neuron from left to right, from the dendrites, through the cell body and come out from the axon. The signal information is transferred from axon to dendrite of second by the means of connection between axon. The connection between two dendrites is called synapse. A human brain contains a large number of processing elements or neurons to process the information from the senses. A human brain have estimated 10–500 billions neurons to process the all information [42]. The artificial neural network concept is derived from the biological neuron. Biological neuron having memory capability between the interconnection of neurons and these connections are named as synaptic weights.

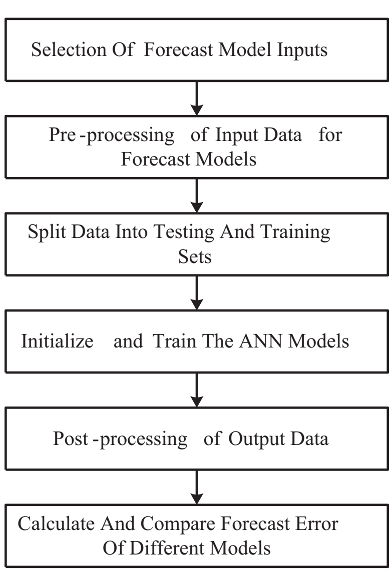


Fig. 10. ANN base load forecast model.

1.11. The artificial neural networks

The neural network consists of input, hidden and output layers connected by the processing elements called neurons as shown in Fig. 12. Neurons in network layers are connected by the synaptic weights and the neural network learning algorithm update their weights in order to map the input/output relationship. The sum of the weighted inputs are processed and applied to the activation function, which generates the output. The weights and biases are adjusted to reduce the error between the generated output and the desired output of the network.

The simple mathematical expression of neuron is described in Equation 3.1. The output of neuron can be calculated as

$$A_i = g\left(\sum_{i=0}^{n} W_{ji*}\, a_j\right) \tag{5}$$

where *Ai* the output of network is, *Wij* is connection weight of *J*th neuron to *I*th layer neuron and *aj* is the input of the neuron. The fundamental unit of neural network may have signal or many inputs and one output. There are two basic operations of the neural network named as training and testing.

Training phase of network is the learning process to correctly map the input/output relationship and neurons of neural network are trained to learn the specific input pattern to generate the suitable output. During the testing phase of network if the network recognizes the taught input pattern correctly, then it will produce the output. However, if the output of network doesn't belong to taught input pattern, then the network is again trained according to generated error. Moreover this neural network training process will until certain learning threshold achieved.

1.12. Activation function

The activation function of neural network is acts as squeezing function to transfer weighted inputs to generate the network outputs. A number of activation functions are available such as; linear function, step function, logistic function, tangent-hyperbolic and sigmoid function etc. However, the activation may vary according to architecture of the neural network, number of inputs and nature of the problem. But there is no rule of thumb defined for activation function selection to produce the better network output. From the literature review, it can be observed that the change in activation function may affect the output of network [43]. Activation function is two step process which is linear combination weighted inputs and transfer function. Moreover, transfer function transforms the all weighted sum inputs into target unit. There are several transfer functions are available and it can selected based on the nature of problem [44]. The classification of different types of transfer functions are given below with their derivatives in Table 3.

1.13. Multi-layer perceptrons neural network

The single layer neural network does not have the capability to learn the complex relationship between the input and output but the multilayer perceptrons neural network (MLPNN) has this ability. Multilayer neural network has one or more than one hidden layers between the input and output layer of the network. Therefore, multilayer neural network having better capability to learn the input pattern and produce better output than the single layer neural network.

Furthermore, multilayer perceptrons neural network is frequently reported for short term load forecast problem [45]. A

Table 1
Application of artificial neural network for smart grid.

S. No	Technique	References	Highlights
1	Three layer ANN based model with Backpropagation learning technique	[22]	ANN based short term load forecast model is proposed for smart grid. Proposed ANN forecast model trained with Backpropagation based learning technique. However, performance of neural network is affected due to intrinsic defects of gradient based such as local minim, slow convergence and higher computational complexity. However, the due to low number samples and poor training of the network the forecast model performance is affected.
2	Context Agent based intelligent model	[23]	Context agent based control technique is proposed for large national infrastructures to self-heal in response to threats, material failures, and other destabilizers.
3	Intelligent Nonlinear Programming	[24]	In this research study, intelligent nonlinear programming technique is designed in order to minimize the energy drawn a substations. The result of proposed intelligent technique is reduction of energy losses by limiting the number of switching operations.
4	ANN and SVM based STLF model for smart grid	[25]	Artificial neural network and Support vector machine based short term forecast model is designed for multiple loads. The objective to this research is to forecast the demand response in smart grids.
5	Neural network trained with Genetic Algorithms, Fuzzy Clustering and Neuron-by-Neuron Algorithms	[26]	A neural network based model is proposed with adaptive training of the network using Genetic Algorithms, Fuzzy Clustering and Neuron-by-Neuron Algorithms for integrating Demand Side Management and Active Management Schemes, allows significant enhancements in energy saving, customers' active participation in the open market and exploitation of renewable energy resources. The performance of proposed NN based Energy Management System and adaptive training algorithm is tested on a 23-bus 11 kV microgrid.
6	Intelligent EMS system	[27] 8ok	This study discussed and critical analyzed the power quality and quantity of power grid transmission network along with their supporting infrastructure. In addition also highlights the information infrastructure requirement to handle the handle ubiquitous phasor measurements recognizing that the quantity and rate of data. This paper also depicts a methodology to transition from currently deployed power network to smart grid network and efficient energy management system.
7	Wavelet Neural Network (WNN)	[28]	Wavelet neural network based (WNN) model is designed using knowledge base of the multi-agent system is aided with constrains functions and power generation forecast using neural networks. In this research work proposed model is designed smart grid management system with renewable energy generation.
8	Multi-Layer Perceptrons Neural Network (MLPNN)	[29]	In this study Multi-Agent System Architecture using Multi-Layer Perceptrons Neural Network (MLPNN) smart grid management virtual power plants with renewable energy resources is proposed in this study. A set of multiagents are embedded with MLP neural network for collaborative energy demand forecasting for domestic and end users.

Table 2
Summary of major ANN developments.

Number	Year	Authors	References	ANN developments
1	1942	McCulloch & Pitts	[31]	Proposed the concept of first artificial neurons.
2	1942	Hebb & Pitts	[32]	Proposed first learning algorithm to memorize the adapting weight values.
3	1958	Rosenblatt	[33]	Developed a first form of artificial network with Perceptron.
4	1959	Lee	[34]	Proposed the Artron.
5	1960	Widrow and Hoff	[35]	Proposed LMS training method and Adaline (Adaptive Linear Neuron).
6	1982	Hopfield	[36]	Design Hopfield neural network.
7	1988	Widrow and Winter	[37]	Design a network using Adeline neurons which is called Madaline.
8	1986	Rumelhart et al.	[38]	Proposed multilayer perceptron base neural network with backpropagation algorithm.
9	1987	Hecht-Nielsen	[39]	Proposed the concept of self organizing mapping using counter propagation network.
10	1988	Chua & Yang	[40]	Design cellular neural network.

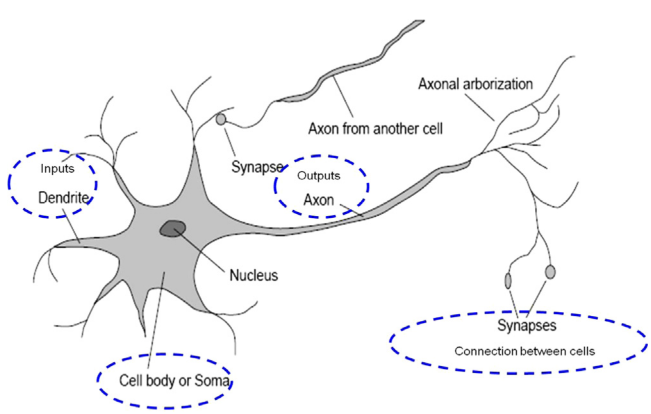


Fig. 11. Structural diagram of neuron [68].

multilayer neural network structure with one input, hidden and output is shown in Fig. 13.

1.14. Types of neural network architecture

Neural network can be divided in two categories based on network architecture:

- Feed forward neural network.
- Feedback neural network.

1.14.1. Feed forward neural network

Feed forward is simplest type of neural network, which may have a one hidden layer or multilayer between input and output

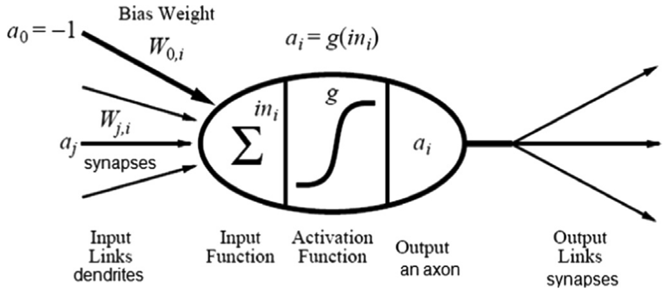


Fig. 12. Basic ANN architecture [71].

layer of the network. In this type of network, the information moves from input to output layer through hidden layer. Moreover, information moves only in forward direction. There is no affect of one layer to other layers because of the absence of feedback cycle or loop.

A feedforward neural network having 3 input, 2 hidden and 3 output layer neuron is shown in Fig. 14. Each neuron of every layer is connected with a forward connection. The hidden layer neuron is model with a nonlinear sigmoid activation function. However, feedforward neural network is extensively used for forecasting and pattern reorganization problem [46,47] (Fig. 15).

1.14.2. Feedback neural network

Feedback neural network allows the information to move in both directions as close loop network architecture as shown in Fig. 15. The output of network influenced the input to achieve the objective function of network by back propagating the error information. However the feedback network is dynamic in nature because of continuous change of the state to achieve the equilibrium. As the change in inputs of network is applied, the network tries to achieve the new equilibrium state from previous state. Feedback neural network are suitable for dynamic and complex processes as well as time varying or time lagged patterns problem [48].

1.15. Learning types of neural network

The learning techniques of neural networks can be divided into two categories as

1. Supervised learning.
2. Unsupervised learning

1.15.1. Supervised learning

Supervised learning is training technique of neural network in which network tried to minimize the MSE for known set of target values. In this type of learning the input and output vectors are specified. Suppose the input vector of neural network is $[x1, x2, x3, \ldots, xm]$ and $[y1, y2, y3, \ldots, ym]$ is the corresponding output vector

$$[y1, y2, y3, \ldots, ym] = [x1, x2, x3, \ldots, xm] * \varepsilon \tag{6}$$

In this input and output relationship,ε is corresponding approximation error between network output and target values [49]. It can be an error vector, which contains the multiple values of error. This error (MSE) is used to update the weight values of network and try to minimize the MSE up to certain acceptable threshold level. Fig. 16 illustrates the basic mechanism of supervised learning of neural network.

As Fig. 16 depicts that, the error of the network feed back into the system to find the correct set of output vector. The weight and bias values of network are updated on the bases of error (MSE) and new set of weight bias values applied to network to generate targeted output. The error is again calculated and fed back to the network to attain the minimum value of error. This process will continue until that, the threshold of error (MSE) is achieved.

Supervised learning technique is widely applied to dynamic systems, especially mapping of nonlinear relationship between input and output of the system. Some of key parameters are needed to evaluate the performance of supervised learning such as: number to iterations per pattern, targeted MSE and objective

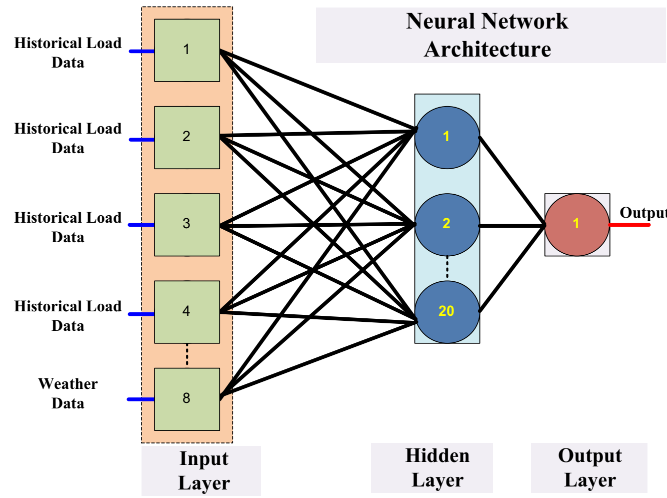


Fig. 13. Multilayer preceptron neural network.

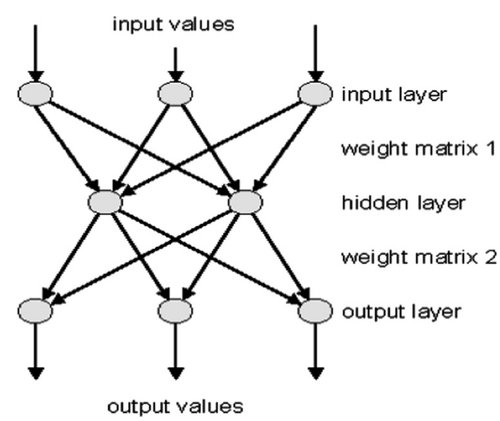


Fig. 14. Feed forward NN structure.

function of network etc. Supervised learning technique is commonly employed to train the neural network.

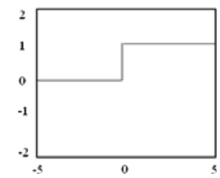
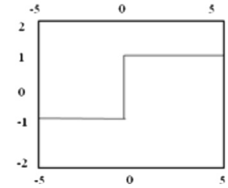
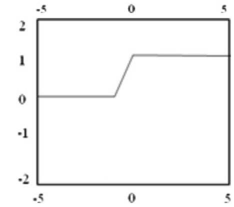
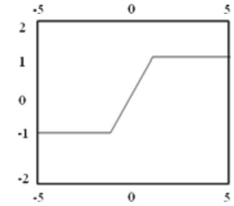
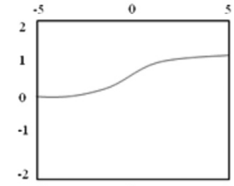
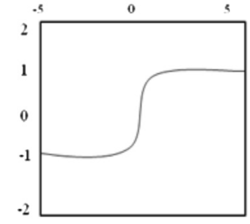
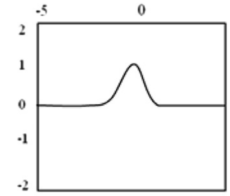
1.15.2. Unsupervised learning

In contrast to supervised learning process, unsupervised learning method of the network does not require the explicit targeted output data as learning mentor. During the unsupervised learning, the system tries to adjust itself according to the different patterns of input and subsequently represents the different input pattern in the form of output of neural network. A number of researches have been worked on unsupervised learning in the field of data visualization, pattern classification as application of unsupervised learning [50].

1.16. Error function

The neural network learning is based on error generated during the training process. Therefore, the network error is defined as mean square of the difference between the targeted and network

Table 3
Artificial neural network transfer functions.

Class	Function	Derivative	Diagram
Unipolar step function	$f(x)=H(x)=\begin{cases}1 & \text{if} \quad ,x>0\\ 0 & \text{if} \quad ,x<0\end{cases}$	$\delta(x)=\begin{cases}1 & \text{if} \quad ,x\neq 0\\ \infty & \text{if} \quad ,x=0\end{cases}$	
Bipolar step function	$f(x)=\ \sin(x)=2H(x)-1$	$\delta(x)=\begin{cases}1 & \text{if} \quad x\neq 0\\ \infty & \text{if} \quad ,x=0\end{cases}$	
Unipolar linear function	$f(x)=H(x)=\begin{cases}0 & \text{if } x<-1\\ 1/2(x+1) & \text{if } \|x\|<1\\ 1 & \text{if } x>1\end{cases}$	$\delta(x)=1/2[H(x+1)-H(x-1)]$	
Bipolar linear	$f(x)=H(x)=\begin{cases}1 \text{ if } x<-1\\ y \text{ if } \|x\|<1\\ 1 \text{ if } x>1\end{cases}$	$\delta(x)=[H(x+1)-H(x-1)]$	
Unipolar sigmoid	$f(x)=\left(1/1+e^{-x}\right)$	$\delta(x)=f(x)(1+f(x))$	
Bipolar sigmoid (hyperbolic tangent)	$f(x)=\ \tanh(x)$	$\delta(x)=\left(1+\left\|f(x)^2\right\|\right)$	
Gaussian radial basis	$f(x)=\exp\left(-\|x-m\|^2/\sigma^2\right)$	$-2(x-m)f(x)/\sigma^2$	

output values. This is called mean square error (MSE) of the network, which is used during the training process of the network. Normally, MSE set as learning error of network and weight values of NN are updated in such a way to achieve the desired learning target [51]. Normally, learning target of network is set to $1*10^{-3}$ as threshold value. The error function of neural network for each learning pattern can be expressed as

$$E(t)=\frac{1}{N}\sum_{i=1}^{N}(O_i^T(t)-O_i(t))^2 \tag{7}$$

where

– $O_i^T(t)$=target value of ith neuron of network output layer.
– $O_i(t)$=network output value of ith neuron of network output layer.
– N=number of training samples used during learning process of the network.

1.17. An overview of the back-propagation ANN model

In 1986, G.E. Hinton, Rumelhart and R.O. Williams proposed the Back-Propagation algorithm to train the neural network. The back propagation neural network consists of input, hidden and output layers connected with each other by synaptic weights. By feed forward propagation, the inputs are propagated to the output through the hidden layers with synaptic weights. The difference between the network and the desired output generates an error back propagated to the hidden layer and the input layer from the output layer. The error is back propagated and weights are updated on the basis of the this back propagated error until the desired output is achieved [52].

The Back propagation learning algorithm used the gradient descent method to update the weights and biases. For the network parameters, the partial derivative of the performance with respect to the weights and biases is calculated. Each node of the network is needed to differentiate in accordance with back propagated error, which is major limitation of back propagation training algorithm [53]. Basic block of back propagation neural network is shown in Fig. 17.

The back propagation algorithm [54] can derived as

Step 1: initialize all weights and the algorithm will continue until the termination condition becomes true.

Step 2: the input signal X_i is received by each neuron in the input layer of the network and is transmitted to the hidden layer.

Step 3: the sum of the input weighted signal (L_j, $J=1,2,3,\ldots,p$)

$$Lmk = Doj + \sum_{i=1}^{n} xi * Dij \tag{8}$$

To compute the output, we have applied the activation function

$$Lj = f(Lm) \tag{9}$$

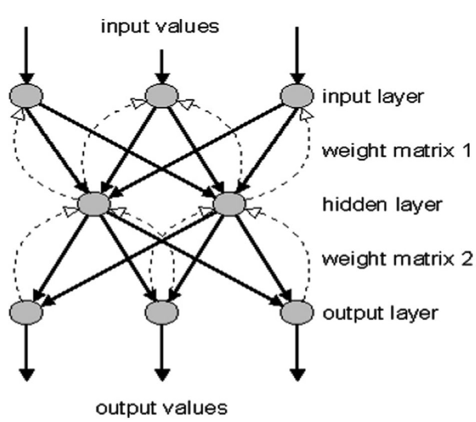


Fig. 15. Feedback NN structure.

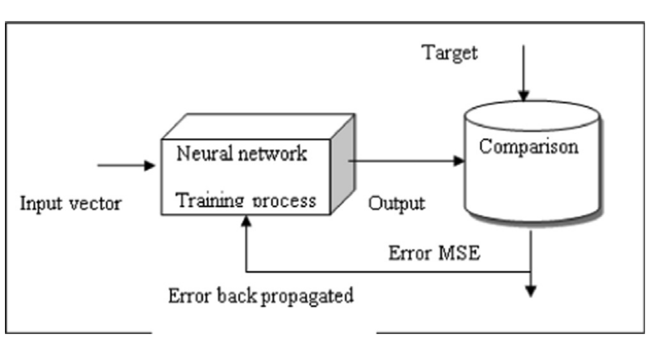


Fig. 16. Schematic diagram of NN supervised learning.

Step 4: the sum of weighted inputs generates the output, accordingly (G_ink where $k=1, 2, 3,\ldots, m$)

$$G\_ink = Wok + \sum_{j=1}^{p} Lj * Wjk \tag{10}$$

And, to compute the output, we have applied the activation function

$$Gk = f(G\_ink) \tag{11}$$

Error back propagation:

Step 5: for error computation, each output unit (Gk where $k=1, 2, 3\ldots, m$) receives a target pattern corresponding to the input training pattern

$$\delta k = (Tk - Gk) f(G\_ink) \tag{12}$$

Calculates the correction term of its weight

$$\Delta Wjk = \alpha \delta k Lj \tag{13}$$

Calculates the correction term of its bias

$$\Delta Wok = \alpha \delta k \tag{14}$$

And sends δk to its units in the layer below

$$\delta\_inj = \sum_{k=1}^{m} \delta Wjk \tag{15}$$

Step 6: each hidden neuron (Lj, where $j=1,2,3,\ldots,p$) in the layer above (from neurons) takes the sum of its delta

$$\delta j = \delta\_inj * f(Lmk) \tag{16}$$

Calculates the correction term of its weight

$$\Delta Dij = \alpha \delta i x i \tag{17}$$

Calculates the correction term of its bias

$$\Delta Doj = \alpha \delta j \tag{18}$$

And updates the weights and biases.

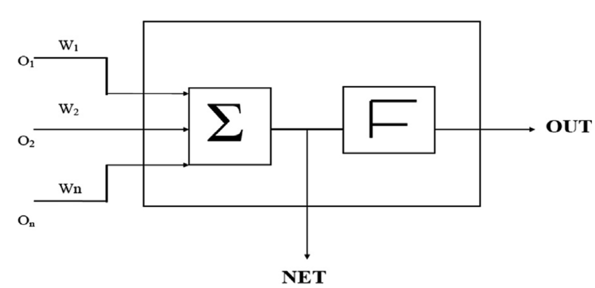


Fig. 17. Basic block of back- propagation neural network.

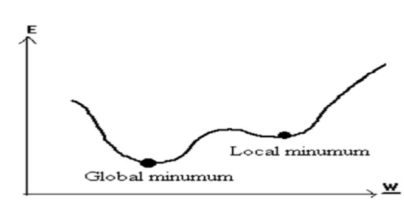


Fig. 18. Global and local minimum in error surface.

Step 7: weights and biases are updated

$$(j=0,\ldots,p)jk(new)=wjk(old)+\Delta wjk \tag{19}$$

Each output unit and each hidden unit also update the weights and biases

$$Oij(new)=oij(old)+\Delta Vij \tag{20}$$

1.18. Back propagation algorithm learning issues

There are some issues with back propagation learning algorithm which affect the training performance of the network as follows;

1. Local minima.
2. Network paralysis.
3. Temporal instability.
4. Generalization and over fitting problem of the neural network.

1.18.1. Local minima

In gradient descent algorithm, the slop of the error is always from higher to lesser error, so that the global minima can be traced out. The weight values of network are adjusted on the basis of small interval in order to avoid get trap in shallow valley called local minima. At local minima point, it is difficult to get out from shallow valley even constant updating the weights. Local minima problem is also one of most important consideration for neural network training algorithm selection [55] (Fig. 17).

The aim of training algorithm is to reach global minimum value on the error surface as shown in Fig. 18. As the figure depicts that, the training objective is to attain the global minimum in order to achieve the higher training performance of the network. However, sometime network gets trapped in to local minimum, which affect the training performance of the network. As result, poor training of neural network will reduce the network performance and affect the output. Moreover, literature review shows that, local minima problem can be avoided by apply better network training technique [56].

1.18.2. Network paralysis

In training process of network, weights of the network can be adjusted for very large values of output, where the derivative of a squashing function is too small. So that, error of network sent back during training process according to its derivative. Sometimes, the training process of network is virtually a standstill that is called network paralysis. This also affects the overall training of the network due to poor learning which leads poor network output [57].

1.18.3. Temporal instability

A process needed for learning of neural network to mimic the entire training set without disturbing, what it has already learned. For example in learning process of network to recognize, the alphabets and network forget the letter A while learning B is called temporal instability. Back propagation training algorithm fails to mimic the complex biological systems. Therefore, back propagation based neural network is not highly suitable for larger target set of values.

1.18.4. Generalization of the network

The major objective of training is to minimize the MSE of network with regards of training set. Generalization is measures of capability of neural network that, network have adjusted itself with respect to different set of inputs. A network is said well generalized, when the output of network is close enough to target values that have not been included in input. The number of factors affecting on generalization such as: size and quality of training data, architecture of network and complexity of network [58].

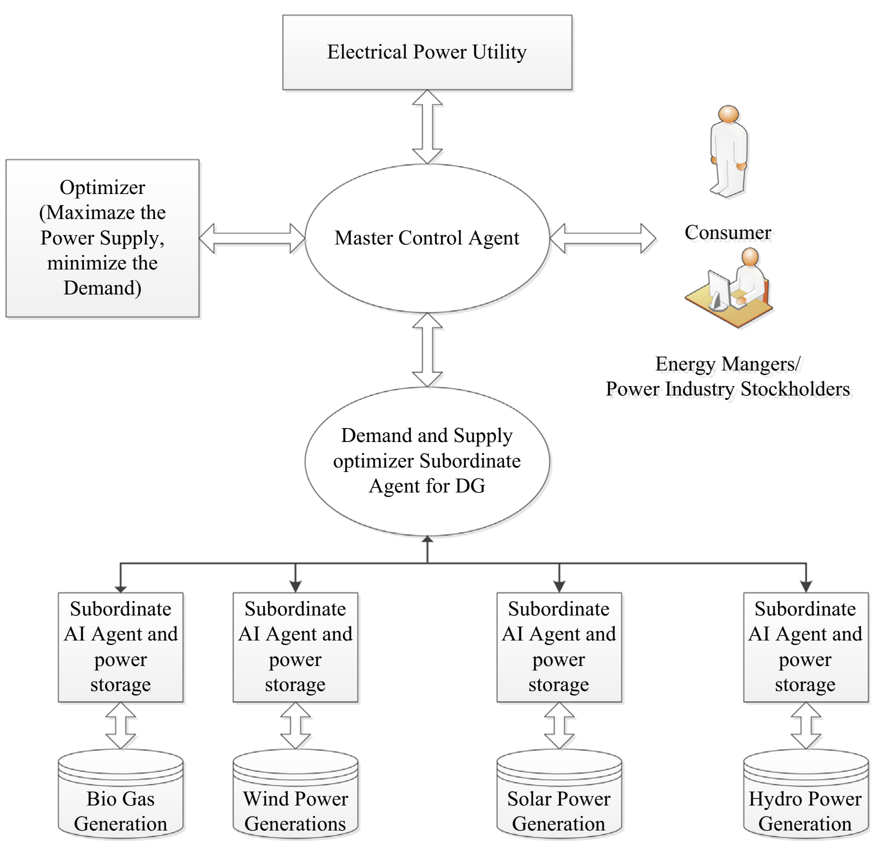


Fig. 19. Control flow of smart power network connected with power utility and distributed generation (DG) resources.

A typical over fitting problem occur neural network, which is unintended memorization of synaptic weight values. Therefore, the output of the network affected even applying suitable training set and training algorithm is applied. The over fitting problem can overcome by the controlling two parameters which length and quality of training data. The over fitting problem can be overcome by applying long training data to the network. However, the training data only include those training patterns, which reflect the real process and irrelevant data must be excluded.

1.19. Conceptual framework of smart power network

Fig. 19 highlights the conceptual framework of artificial intelligence based electrical power utility coordination setup. The key objective function of master controller is to maximize the power supply cost function and minimize the demand of different types of consumers. Several population based multi-objective has been implemented for different controlling application such as multi objective genetic algorithm (MOGA), multi-objective particle swam optimization (MOPSO), multi objective ant bee colony optimization (MOABC) etc [59,60].

The objective function of master agent controller is given below

$$Overall\_Power\_Supply = \max \sum_{i=1}^{h} w(h) * power\_supply(h)$$

$$Overall\_demand = \min \sum_{i=1}^{h} w(h) * Demand(h)$$

where $Demand(h) \le Overall\_Demand(h)$ and $i = 1, 2, 3, ..., h$.

1.19.1. Master control agent

In proposed conceptual framework of smart power network, electrical power utility is connected with master control agent. Master control agent is responsible communicate with all AI based subordinate controllers.

1.19.2. Subordinate control agent

The interactions of the hierarchical agents operate in modes of operation classified as autonomous mode and non autonomous mode. The information of generation of specific power generation parameters such generated power, current frequency and voltage along with other necessary parameters is share with master control agent. In addition, Subordinate control agent also responsible to coordinate with master control agent and implements the set of instructions of master controller. The important information from agents has been send to the master controller and returned to agents after processing to make actions accordingly. Moreover, the high speed of communication between master and subordinate controllers can reduce the control delay and improve the response time of the controllers. In addition, the online monitoring can be achieved by the energy mangers. Subordinate controllers can be operated in autonomous mode of operation in case fault in communication link between master and subordinate agents. It can also be operated when there is delay in receiving set of instructions from master control agent or fault in master agent. On the other side, subordinate controller will operated in non autonomous mode of operation. There are some research studies conducted on smart grid control schemes [61,62].

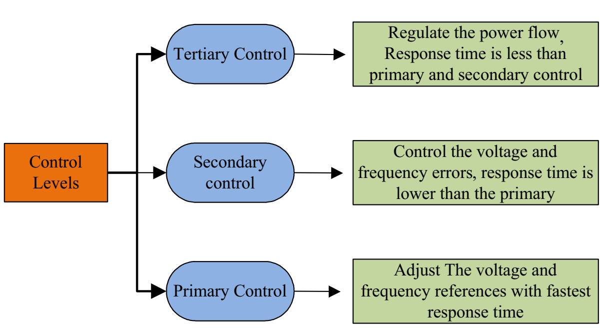


Fig. 20. Control level of future generation power grid.

1.19.3. Energy mangers

Energy manger or power industry stockholders can manage the trade the power between different power producers. These mangers can also implement national and state energy policy by giving the set of instructions to master agent controller.

1.20. Control strategy of smart grid/DG connected microgrid

There are three levels of control for smart grid or distributed grid connected microgrid. These control level with their function are given below and shown in Fig. 20.

1.20.1. Primary control

Objective of first level control is to adjust the frequency and amplitude of the voltage references according to IEC/ISO 62264 std. level one control [63]. The prime requirement of the primary is to provide the fastest response to changes occur in sources or demand of the power system. In addition the primary control is also to create balance between distributed generation resources and energy storage elements.

In island mode, the optimal performance of primary control can be achieved by the batteries state of charge (SOC) [64].

1.20.2. Secondary control

The objective of second level control the voltage and frequency errors in addition with regulation of operational limit values. Secondary level control ensures the voltage and frequency deviation towards to zero. However reposes time of secondary level control is lower than the primary level control due to battery and availability of primary sources [65].

1.20.3. Tertiary control

Tertiary level control is used to regulate the power the flow by regulating hr frequency and voltage in non autonomous mode of operation according to level three of IEC/ISO62264 std. Tertiary control is last control of grid in non autonomous mode of operation which also ensure the economical operation of the power grid [63].

1.21. Neural network learning techniques

ANN training is the learning process to extract inherent complex relationship among input variables by which network can calculate the difference between actual and desired output. The error function is generated with the difference of desired and network output. Conventional Back Propagation method is used for training of neural network based on gradient descent or conjugate gradient descent learning method. These methods are based on partial derivative of output with respect to the weights and biases value. The major drawback of back propagation (BP) learning algorithm e.g. very slow in training process, depends upon the initial parameters values by their possible chance neural network to get trapped in local minima.

1.22. Hybrid ANN based techniques for STLF

Hybrid techniques are proposed with the combination of superior attributes of two or more algorithms. In previously published research, researcher integrates the neural network with other optimization techniques to get more efficient forecast model. It can be conclude that from previously published research, the hybridization of two or more techniques shows better results than the conventional statistical techniques for load forecast problem. The forecast model accuracy may depend on several factors such network structure, learning algorithm, network parameters and quality of applied historical load data [66].

In this section, hybrid models are examined for STLF. Recent hybrid training methods for ANN for short term load forecasting can be classified as follows:

- ANN with fuzzy and genetic algorithm.
- ANN with expert system and regression technique.
- ANN with wavelet and time series.
- ANN with support vector machine and artificial immune system.
- ANN with genetic algorithms.
- ANN with Gradient Based Learning Techniques.

1.22.1. ANN with fuzzy logic and genetic algorithm

A fuzzy logic based load forecast with ANN models are generally developed to classify a large input load data set to accurately predict the load demand. Yang et al. [67] constructed a forecasting model to consider the effect of weather and holidays on forecast accuracy. Fuzzy logic membership functions and rule bases are constructed for temperature and holiday factor. At the second stage, ANN model is used to predict the hourly load demand. Hourly load forecast results show that, ANN model with fuzzy logic produces better forecast results than the single ANN model. As stated in Jain et al. [68] the fuzzy adaptive inference system and similar day effect, which takes account of the effect of humidity and temperature. Fuzzy inference system is also used to improve the similar day load curve which increases the forecast accuracy. In order to encounter the uncertainties and unexpected behavior of power system Khosravi et al. [69] presented a forecasting model to increase the accuracy and handling of uncertainties. Historical load demand, weather information and yearly calendar events are considered as model inputs. The proposed model handles the uncertainties of a power system, which significantly improve the accuracy.

Senjyu et al. [70] proposed a hybrid neural network, which is a combination of neural network with fuzzy logic to enhance the accuracy. The similar day approach is used to select correlated inputs for better training data. The proposed methodology shows a considerable improvement in forecasting accuracy over a test period.

Khotanzad et al. [71] developed neuro fuzzy based a short term load forecast model for deregulated and price sensitive electricity market. In this research, the impact of electricity price on load consumption is considered to design an accurate load forecast model. It is observed that, the load consumption pattern is different between fixed price and price sensitive (PS) electricity market. Forecast model is designed at two stages. ANNSTLF is used in first stage and genetic algorithm is used to optimize the parameters of fuzzy logic rules and membership functions in the second stage. The performance of proposed neuro fuzzy based forecast model is tested on three different types of load. The results show that, the proposed neuro fuzzy based forecast model shows better performance in price sensitive environment than the price-insensitive (PIS) electricity market.

Yang et al. [72] proposed a neural network based short term load forecast model with fuzzy logic. Fuzzy logic membership function is designed in such a way that, they will select most influencing inputs of forecast model. These inputs have great affect on hourly load demand such as air temperature, working or off day, anomalous day and previous correlated load inputs. The output data of fuzzy logic is used to train neural network to forecast working day, off day and special day load demand. By applying fuzzy logic input preprocessing method, the neural network learning time and computational complexity is reduced. A significant improvement in forecast accuracy can be observed by using integrated neural network and fuzzy logic based forecast model than the conventional neural network based forecast model. From the simulation results it also can observed that, the proposed model shows higher forecast MAPE for special days load forecast than the working days due to uncertain load pattern during the special days.

Hooshmand et al. [73] proposed a two stage hybrid intelligent short term load forecast model with forecast horizon of 24 h. At the first stage, wavelet transform and artificial neural network is used as primary level forecaster. Historical load data and weather variables such as daily mean temperature, maximum temperature mean humidity and mean wind speed are used as forecast model inputs. After that, adaptive fuzzy inference system (AFIS) and similar hour method is used to improve the results of primary forecast model. From the simulation results it can be observed that, adaptive fuzzy inference system (ANFIS), wavelet transform (WT) and similar hour method improve the forecast results of primary forecast model significantly. Furthermore, it is also observed that the abrupt change in weather condition will result of higher forecast error. The proposed forecast model achieves the forecast MAPE up to 1.703%, which is relatively lower than the conventional neural network based forecast models.

Wi et al. [74] proposed a model to forecast the holiday load demand with fuzzy polynomial regression and mahalanobis distance method to incorporate a dominant weather feature. In this research, proposed methodology is designed to improve the forecast accuracy of the model for holidays load forecast because few number of similar data patterns are available for proper training of the model. Therefore, dominant weather feature is used to improve the output of fuzzy polynomial regression model. Moreover, in order to improve the forecast model performance, an adjustment procedure is defined to deal with sudden changes in weather variables data. Several case studies are designed to forecast the load demand of holidays such as; new year day, lunar new year's day, memorial day, Buddha's day, children's day and Christmas day. The simulations results show that, the proposed forecast model give better performance fuzzy linear system and expert knowledge based system. However, the impact of weather forecast is not considered in this research, which may affect the forecast accuracy of model.

1.22.2. ANN with expert system and regression technique

In [75] proposed a expert system for short term load forecast model named as LOFY is used to forecast the load demand with three different time horizons i.e. daily, weekly and special day forecast model. The objective of proposed model is to archive precise forecast results. This is a well known fact that, there is no unique single method which ensures the high forecast accuracy for different types of day. Secondly experts system provides the better forecast results than other theoretical method. The Lofy expert models contains the several forecast models and select the best suited model on the basis of expert's knowledge base in the form of fuzzy rules. It employs the ANN and regression model for weather sensitive days and fuzzy logic base model for special days. The proposed model gives the forecast mean absolute percentage error (MAPE) 1.86%, 1.64%, 2.0% for daily, ordinary day and weekdays forecast respectively.

Mor et al. [76] develop a hybrid load forecast model using a multi-layer preceptron (MLP) and globally optimal regression tree. In order to enhance the forecast accuracy of proposed model, data mining technique is used to search the optimal parameters. The forecasting results show that, the proposed technique produces better forecast results than the CART-MLP and MLP in terms of the average and maximum forecast error. The employed method reduces the forecast error up to 7.17% to 5.20% compared to MLP.

Heru et al. [77] proposed a hybrid expert system for short term load forecast using artificial neural network and fuzzy expert system. The proposed model forecast the load demand using trained radial basis function (RBF) network and fuzzy expert system correct the forecast output of RBF network. It is essential due to large variation of temperature and holidays load demand. Simulations results shows the proposed model gives maximum MAPE of 2.09% for one week ahead load forecast and average forecast error up to 1.58%.

Ghanbari et al. [78] developed an intelligent load forecast expert system by integrating ant colony optimization (ACO), genetic algorithm (GA) and fuzzy logic called ACO-GA. The working principle of proposed technique is similar to adaptive neuro fuzzy logic inference system (ANFIS) where genetic algorithm is used to learn the fuzzy membership and scaling factor. Ant colony optimization technique is applied to obtain the suitable rule base of fuzzy and fuzzy logic is applied to map the model input/output relationship. The simulation results that, the propose integrated expert system shows higher forecast accuracy for all test case studies than the adaptive neuro fuzzy inference system.

Sfetsos et al. [79] presents a hybrid STLF technique using linear regression and ANN. The proposed techniques assign the patterns to each cluster based on the distance from the hyper plane, which is defined by governing equation of each cluster. California grid data is used to train and validate the forecast model. The forecast results show that 7.54% improvement was found in forecast results using ANN model with 12 clusters. For New York load data, the eight clusters show the 9.88% improvement in forecast result but lower than the respective ANN model.

Wie et al. [77] proposed a short term load forecast model based on seasonal exponential adjustment method (SEAM) and regression model. In this study, seasonal exponential adjustment method is used to compensate the seasonal variation impact on load demand pattern and regression model is employed for one week ahead load forecast. Furthermore, the simulation results show that, there is significant improvement in forecast accuracy of proposed model for one day ahead load forecast studies than the separate forecast techniques. Moreover, the proposed combined model achieves minimum mean absolute percentage error (MAPE) up to 4.88%.

Tripathi et al. [80] developed a generalized regression and probabilistic neural networks based short term load forecast model in order to predict the load demand of Australia's Victoria grid. Therefore, in order to improve the forecast accuracy, electricity prices are included along with previous load and respective weather data as forecast model inputs. Moreover, different case studies are designed to forecast the load demand of week days and weekends. For the validation purpose, proposed model forecast results are compared with ANN-Fuzzy, ARMA model and back propagation based neural network. Therefore, proposed model achieve higher forecast accuracy than the comparative techniques and produces the minimum MAPE up to 1.85%.

1.22.3. ANN with wavelet and time series

Du Tao et al. [81] present a hybrid model for STLF by combining the strengths of wavelet analysis and ANN. The large load data is decomposed into smaller data collections by applying the wavelet multi-resolution analysis and provide the sub collections of load data to ANN models for load forecast. At the final stage the forecasting results are achieved by summing up all the sub forecast models. This hybrid approach shows better convergence rate and accelerates the training time of ANN models. For 24 h ahead load forecast, smaller 24 networks are designed and each sub collection of data is provided to train the network. The proposed model is relatively much easier to optimally construct and train than the single large network. The results shows that, the average per month forecast error is 1.90% to 2.24% and per day error in the range of 1.65% to 2.17%.

Abu El Magd et al. [82] presents a hybrid method to forecast the load demand of weekdays as well as weekends and public holiday load demand. The proposed hybrid technique is combination of time series and ANN. In this research the auto-correlation analysis is used for appropriate input selection of forecast model. The forecast results of holiday, weekends and Mondays prediction are compared with other techniques. The proposed technique produces the mean relative percentage error (MRPE) of 2.07% including holidays

Paparoditis et al. [83] proposed a similar shape functional time series based short term load forecast model. The expected load segment shape is predicted using weighted average of similar historical daily load segments. The similar past load segments are identified from the available history of the observed load segments. The proposed functional time series load forecast method is applied on historical daily load data of Cyprus grid. The simulation results shows that, the functional time series based forecast model give relatively higher forecast accuracy than the functional wavelet kernel time series method.

Deng et al. [84] presents a time series based short term load forecast model for Singapore grid as case study. In this study, two forecast models are presented such as; multiplicative decomposition model and Box-Jenkins ARIMA time series model. In order to analyze the performance of proposed models, several load forecast case studies are designed such week day, weekends and special day load forecast case studies. The overall forecast error MAPE is achieved up to 3.40%. Moreover, it is also observed that, multiplicative decomposition model outperform than the seasonal ARIMA for different forecast case studies.

Amjady et al. [85] proposed short term hourly load forecasting technique using time series modeling with peak load estimation capability. In this research, modified auto regressive integrated moving average based forecast model is used to predict the load demand of weekdays, weekends, public holidays and special days. The load demand variations during working days, weekends, public holidays, special events (Islamic events such Eid celebrations, Muharram etc) are also studied. Moreover, in order to increase the forecast accuracy, operator estimation is also included along with historical load and temperature data. A large variation in load pattern is observed during cold and hot day, working and off days, special days than the routine electricity consumption pattern. The forecast results shows that, the modified ARIMA based forecast model shows better results than the ARIMA and give forecast MAPE up to 1.98% for public holiday case study.

Espinoza et al. [86] presented a short term load forecast model based on the periodic time series for profile identification and customer segmentation. In this the study, single PAR model is used to predict the load demand under various load conditions. Single PAR model consists the 24 set of seasonal equations and 48 historical load values are applies to each equation to design the appropriate short term load forecast model. The performance of proposed model is analyzed for Belgian national grid operator ELIA over 40,000 time series data points. Moreover, 24 h and 168 h ahead load forecast studies are designed in order to assess the quality of proposed model and minimum error up to 3% achieved. However, the respective weather information is not included to design the efficient forecast model.

1.22.4. ANN with support vector machine and artificial immune system

Recently the reported research using support vector machine and more on support vector regression are used for STLF problem. Support vector machines are normally used for data categorization and regression. Chen et al. [87] applied support vector regression for STLF and the model inputs are previous seven day load demand, weather data and calendar information. The best approach reached the MAPE of 1.95%. A validation procedure is also presented to judge the either weather inputs are integrated or not. The two different forecasted load patterns are also identified due to different training data of forecasting model.

Wang et al. [88] proposed a hybrid load forecast model using support vector regression (SVR) and differential evolution algorithm (DE). Differential evolution algorithm is used to identify the suitable parameters of support vector regression based forecast model. Furthermore, in order to analyze the performance of proposed DESVR based forecast model, the forecast results are compared with back propagation based neural network, support vector regression and regression load forecast model. The proposed SESVR based forecast model achieves the forecast accuracy up to 1.8%. It also outperforms than all comparative techniques in terms forecast accuracy, fast convergence and generalization capability. However, weather related data, economic growth and other exogenous variable are considered as forecast model inputs, which affect the forecast accuracy.

Niu et al. [89] presents an integrated short term load forecasting technique using support vector machine (SWM) and ant colony optimization. An ant colony optimization technique is used to pre process the bulky input data of forecast model to increase the model efficiency. In this proposed method, system mining technique is used to identify the similar and correlated metrological features. This preprocessed load and weather data is applied to SVM based short term load forecast to predict the 24 h ahead load demand. This research shows that, ant colony optimization technique gives better performance than the fuzzy-rough method, an entropy-based feature selector and a transformation-based reduction method. The proposed forecast results are compared such as single SVM and back propagation neural network for several case studies. Therefore, the proposed technique give better forecast results than benchmark technique and minimum MAPE 1.98% is achieved.

The immune system is based on the living being's immune process. According to the immune system, the solution of the problem is treated as an antibody and the problem as an antigen. The system will produce antibodies to resolve and control the antigen. There are actions and executions between the antibodies that controlled by the antigen. If the concentration of the antibodies increases then the actions and executions also increase. In [90] neural network model is proposed and trained by the artificial immune system to achieve a higher accuracy. In [29] it is propose to have a model to achieve higher accuracy, lesser input load data requirement and faster convergence. The hybrid artificial immune system (AIS) is proposed which is combination of the back propagation method with the artificial immune system. The hybrid methodology shows that the genetic algorithm (GA) and particle swarm optimization (PSO) require 150 iterations and 36 data sets but the hybrid AIS takes only 6 iterations and 21 data sets to converge the same extent.

Dudek et al. [91] proposed a novel artificial immune system (AIS) based short term load forecast model to predict the hourly load demand of a week. In this proposed technique, antigen of AIS which contains the time series load sequences are recognized by the trained immune system with historical load patterns. The new generated incomplete antigen contains the first part of load sequence and second part of forecast sequence is reconstructed by activated antigens. In order to evaluate the performance of proposed forecast model is applied to different load patterns and minimum MAPE is 1.77% achieved. However, AIS based forecast model shows several disadvantages, such as limited ability of extrapolation and some time series load data pattern is not presented in immune memory. Moreover, weather parameters and other exogenous variables are not included in this research, which greatly affect the forecast accuracy of model.

1.22.5. ANN with genetic algorithm

The genetic algorithm (GA) is a random search technique that is widely used to find the optimal solution. It is a class of population-based algorithm and finds the optimal solution on the basis of the optimal point of a population. The genetic algorithm is also applied along with other population based techniques such as ant colony optimization (ACO), fish swarm optimization etc for different real world optimization problems. Population-based algorithms like GA and randomized search-based algorithms are expected to be robust against a convergence in the global optima.

In [92] GA and PSO to reduce the training time of the neural network and to converge optimally have trained multi-layer perceptron (MLP) models. The genetic algorithm gives better accuracy with a MAPE of 3.19% but is slow in training. However, the particle swarm optimization shows much faster training but is lower in accuracy with a MAPE of 4.25%. In this model, meteorological conditions are not considered so it is possible that accuracy will be affected in cases of abrupt weather changes.

Table 4
Highlights of ANN with Genetic based forecast model.

Number	Technique	References	Highlights
1	Genetic algorithm with support vector regression	[11]	In this study short term load forecast model is proposed using Chaotic Genetic algorithm (CGA) with support vector regression technique (SVR). The objective the study the enhance the performance of forecast model by overcoming the problems of premature convergence, slowly reaching the global optimal solution or trapping into a local optimum. In addition SVRCGA based forecast model depicts the better performance comparable forecast models.
2	ANN with Genetic and Backpropagation model	[12]	An artificial neural network based short term load forecast model is proposed by using improved genetic algorithm along with backpropagation (BP) training technique. In order to avoid of local minima problem of BP based neural network overcome with global search capability of optimized genetic algorithm. The proposed forecast model depicts the better prediction results than other forecast models for Shangai power production.
3	Neural fuzzy Network (NFN) with improved genetic algorithm (GA).	[78]	The GA technique is utilized to obtain the optimal set of fuzzy rules and fuzzy logic employed to handle variable linguistic information in load forecast. The forecast result shows that, the MAPE of proposed hybrid technique is 1.56%
4	Chaotic genetic algorithm simulated annealing (CGASA) with support vector regression	[13]	Author proposed a forecast model to enhance the forecast accuracy of the model with Chaotic genetic algorithm simulated annealing (CGASA) with support vector regression based short term load forecast model. The research finding highlights that, proposed SSVRCGASA based forecast model illustrate improved forecast results than the ARIMA and TF-ε-SVR-SA models.

Table 5
Highlights of load forecast models.

Number	Technique	References	Highlights
1	Linear	[98,99]	Linear forecast models is easy to built but it produces higher forecast error due inability to map the complex input and output relationship.
2	Nonlinear	[100,101]	Nonlinear forecast models gives higher forecast accuracy than the linear models and better capability to build the relationship between model output and affecting variables.
3	Fuzzy	[102–104]	Fuzzy techniques are used to solve the uncertainties in load demand forecast. It also provides the better forecast results than the linear and non linear based forecast models.
4	Ann	[105,106]	ANN produces higher forecast accuracy and gives better results for other applications as it has capability to map the complex input/output relationship through its training process.
5	Support Vector Machine	[89,107]	Support vector machines are generally used for data classification and regression
6	Time Series	[108,109]	Produces higher forecast accuracy under normal condition of exogenous variable. However forecast accuracy is affected due to abrupt change in affecting variables such as; weather variables for load forecast.
7	Wavelet Based Neural Networks (WNN)	[110–112]	Provide a better way to analyze the non stationary components of electrical load using multi-resolution decomposition. WNN based neural network shows better forecast results than the conventional neural network based forecast model.
8	Regression Technique	[104,113]	Load forecast model based on regression techniques are employed to extract the complex relationship between electrical load and exogenous variables.
9	Artificial Immune System	[91,114,115]	AIS system shows superior pattern recognition and memorization capabilities through variation of the number and affinities of the antibodies.
10	Gradient Based Learning Techniques of NN	[116–119]	Gradient based and conjugate gradient based training techniques of neural network widely used to train network and also applied for load forecasting problem. However, performance of neural network is affected due to intrinsic defects of gradient based such as local minim, slow convergence and higher computational complexity.
11	Population based learning algorithm for NN training	[89,111,120]	Population based algorithm utilized to improve the training capability of neural network to enhance the performance of forecast model such as particle swarm optimization (PSO), genetic algorithm (GA), ant bee colony optimization (ABC) etc. these algorithm shows better performance than the conventional training for forecasting problems.

Ling et al. [93] proposed a hybrid forecast technique with combination of neural fuzzy network (NFN) and improved genetic algorithm (GA). The GA technique is utilized to obtain the optimal set of fuzzy rules and fuzzy logic employed to handle variable linguistic information in load forecast. The forecast result shows that, the MAPE of proposed hybrid technique is 1.56%.

Li et al. [94] proposed a genetic algorithm (GA) and grey model (GM) based short term load forecast technique. In this proposed technique, genetic algorithm is used to find the optimal α value of grey model to enhance the forecast model capability. Furthermore, one-point linearity arithmetical crossover is used in order to increase the speed of genetic operators (crossover and mutation). The proposed forecast model results are compared with genetic algorithm and grey model based forecast technique for 24 h ahead case studies. However, it can be observe that the proposed model gives better forecast results than benchmark techniques.: Highlights of GA ANN models are given in Table 4.

Ling et al. [95] presents a short term load forecast model using genetic algorithm (GA) based neural network. Genetic algorithm is used to train the neural network and mean absolute percentage error of network is assigned as objective function of GA. Genetic operators (crossover and mutation) are applied to achieve the fitness function of network. Moreover, genetic algorithm runs until the training MAPE of network is dropped blow then threshold value. In this study, historical load and respective weather data such as temperature and rainfall index is used to train the network. Moreover, 24 h ahead load forecast case studies are designed for weekdays and weekends in order to measure the performance proposed model. The proposed GANN forecast model give the minimum MAPE up to 2.867% (Table 5).

1.22.6. ANN with gradient based learning techniques

Gradient based techniques are one of most widely used learning methods of neural network. Back propagation is commonly used training of the neural network which is based on gradient based learning algorithm. In these learning techniques, weights and biases of the neural network are calculated based on gradient descent algorithm. These network parameters are calculated based on the partial derivative of the performance function of the network with respect to the weight and biases value. Each node of the network is needed to differentiate in accordance with back propagated error, which is major limitation of back propagation training algorithm.

Saini et al. [96] develop a forecast model to predict the peak load demand using artificial neural network. In this study, Levenberg Marquardt backpropagation and one step scent technique is used to train the neural network. In order to enhance the forecast accuracy of NN based forecast, weather parameters, type of day and the previous day peak load demand are included as training data. Moreover, input preprocessing is also applied on training data to increase the training capability of the network. By applying preprocessing on input data of forecast model, network training time, simple network architecture and higher network training capability due to existence of similar data pattern in training data is achieved. In order to analyze the performance of anticipated forecast model, several load forecast case studies from one to seven day ahead are designed. The average forecast MAPE of proposed forecast model is achieved up to 2.87%.

Liu et al. [97] proposed a forecast model to predict the hourly load, daily load and weekly load demand of Ontario, Canada grid. In this study authors develop neural network based forecast model using Levenberg Marquardt as a training technique of network. Moreover, authors also analyzed the load profile of one day, one week, one month and three years from 2004 to 2006 Ontario grid. From load profile analysis, repeating load pattern of power consumption and seasonality trend can be observed. The network is trained with historical load data, where 75% data length is used to train the network and 25% for network testing. Simulations results show that, hourly load forecast MAPE lies within the range of $\pm$5% and 95% of confidence interval of forecast model.

Bashir and El-Hawary [128] purposed a wavelet neural network based forecast model with Backpropagation as training algorithm. Wavelet neural network shows better performance in terms of higher generalization capability and fast convergence speed than the feed forward neural network. The training of wavelet neural network is carried with Levenberg Marquardt backpropagation technique with historical load and respective weather data. Moreover, in order to evaluate the performance of proposed WNN's based forecast model with ANN model. The proposed WNN's based forecast model takes 750 epochs to train the network while ANN model takes 2500 epochs to achieve the same performance goal. WNN's based forecast model shows higher forecast accuracy, fast convergence and better generalization than the ANN's model. However, proposed technique is dependent on initial weight values and computational expensive as it requires the gradient information to update the NN weight bias values. Highlights of load forecast model are presented in Table 5.

1.23. Future directions

So, hoping to give an idea and given below suggestions can be considered for future research directions.

1. Metrological factors have great influence on load consumption patterns. So that in order to enhance the performance of forecast model, other parameters can be considered as forecast model input such as absolute temperature, humidity information, wind speed, cloud cover, rainfall, and the human body index [121].
2. Hybridization of powerful heuristic and evolutionary optimization techniques can be explored for dynamic learning of neural network, which may enhance the forecast model output [122].
3. A hybrid optimization technique can be employed to optimize the neural network architecture and suitable transfer function neural network also needs to be investigated [123].
4. In deregulated electricity market, electricity price is also one of important influential parameter on load demand. In future work, electricity price can also be considered with other influential parameters on load demand [124].
5. Fuzzy logic can be utilized for dynamic input selection according to forecast horizon and optimal input data length of forecast model also needs to be investigated.
6. Electrical load forecasting can explored to implement the concept of smart grids and smart building to integrate in future generation power systems [125].
7. Recent researches also focus on consumer demand side energy management to enhance the quality of power system. Future work may consider the implantation of load forecast for demand side management of the consumers [126].

1.24. Conclusion and summary

A number of AI techniques have been reviewed in this study for load forecasting application. Furthermore it can observe that, AI techniques have been applied in a wide range of research areas of electrical load forecasting with certain success level. The findings of comprehensive literature review shows that, there is a clear shift to improve the training capability of neural network in order to achieve promising results of load forecast model than the conventional techniques. Moreover, a number of hybrid forecast techniques are applied in order to increase the forecast accuracy. However, these methods are not completely addressing the aforementioned problems. Backpropagation (BP) training algorithm is widely used to train the NN. BP trained neural network show the several defects named as; dependence on initial weight values, lower convergence, higher computational complexity, local minima problem and lower network training performance. However, integrated approaches or two stage load forecast model may utilize to enhance the forecast results.

A new research trend can analyzed that, the heuristic search and population based optimization learning algorithms of ANN for STLF problem provide much better results than the gradient decent (back propagation). Moreover, forecast accuracy of the model may enhanced with better training of ANN, better input selection of forecast model and optimized neural network architecture. However, the performances of ANN based forecast model can be increased by encounter these problems such as; dependence on initialization of weight values, local minima problem, poor generalization of the network and slow convergence.

It is also conclude that there are several issues needed to be addressed along with forecast accuracy such as network complexity, better training algorithm, convergence rate and selection of highly correlated forecast model inputs to produce the higher forecast results. The implementation of the accurate can save significant amount of energy and wastage and CO2 emissions as power system contributes highest amount about 32% of total [127].

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