



# **Artificial Neural Network Approach for Load Forecasting in Demand Side Management**

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**ABSTRACT:** To meet the fast growing demand of energy, smart techniques need to be adopted that are in compliance with the environment and energy conservation. In this paper, an autonomous demand-side energy management to encourage users to willingly modify their electricity consumption without compromising with service quality and customer satisfaction using load forecasting. The projected distributed demand side energy management (DSM) strategy gives each consumer an option to simply apply its best response strategy to current electric Load and tariff in the power distribution system. Using NN and ACO technique on load prediction, it is obtained that an area-load based pricing method is beneficial for both electric utility and consumer. Simulation results shows that the proposed approach can maximize load factor and reduce total energy cost as well as user's daily electricity charges.

**KEYWORDS:** Demand Side Management (DSM), Neural Network (NN), load factor.

## **I.INTRODUCTION**

In the fabric of liberalized electricity market, there is a need for sustainable environment with adoption and implementation of energy efficient resources. Evolution of smart grid has provided a breakthrough in the existing power system in order to maintain a reliable, uninterrupted and secure infrastructure. However, in order to keep pace with the modern challenges of meeting dynamic electricity demand, techniques like advancement in automation, data communication and distributed generation have been effectively deployed to accommodate suppliers and consumers from a wide range of scenarios, to anticipate and respond to changing operating conditions with greater economic efficiency and energy usage. Demand side management (DSM) proves advantageous and economically viable for strategically and intelligently influencing the load instead of investing money on setting up a new power generating unit [2]. DSM primarily includes different pricing methods adopted by utilities to ensure efficient network utilization. Different pricing methods commonly used by utilities are: flat-rate method, TOU (time of use) method and load based methods. Time of use tariffs and flat rates techniques are used less as they may not necessarily cut down the peak of energy usage but would adversely create a steep rise in off-peak hours. Consequently, demand response programs were introduced which are based on load based pricing instead of time base, i.e., electricity tariffs vary proportionally to the power system load as specified in the desired function. The load-forecasting task depends on past and current information about variables that affect the load for a period of time. A Forecasting system can be carried out as follows: obtain and analyze the historical data; pre-processing and normalizing of the information; choosing the training and testing set; choosing the type of network and its parameters; choosing a suitable learning algorithm; and finally, implementation.

It does not necessarily reduce energy consumption but influences the consumption pattern [9]. Appropriate load shifting becomes a cause of major concern as PHEVs (plug-in hybrid electric vehicles) come into picture due to their high charging rate. They acts as a significant load on existing distribution system, deteriorating the load factor accordingly and thus causing degradation of power quality, fluctuation in system frequency and voltage, sufficient loss to the utility and consumer and thereby creating imbalance in the power distribution system. In order to maintain a balance between demand and supply to certain extent, dynamic load control (DLC) strategy was adopted [2], where in accordance to the contractual arrangement, the utility can remotely control the operations on certain priority-specified household appliances. Consumer privacy is considered bottle-neck for this method. With limitations of other pricing methods and improvements in smart metering technologies, load-based pricing are becoming more popular and



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imperative. Different pricing methods have been studied in literature. For instance, day ahead pricing method is adopted to provide assistance to retail providers or DISCOMs (DISTRIBUTION COMPANIES) [4]. To meet the fluctuating load, utilities need to ensure sufficient transmission and generation resources to meet forecasted demand. Resource procurements should be done economically to optimize the operational cost. Since the economy of the operation and control of power systems are greatly affected by load demand, significant savings can be attained by increasing the accuracy of load forecast. High forecast error can lead to either over conservative or unreliable operation. For example, higher estimation of load can cause unnecessary startup of additional generation units or excessive energy purchase. On the other side, low estimation results in insufficient spinning reserve, which is contrary to safe operation requirements. Lack of supply due to errors in load forecast can also lead to near real time procurement, which is generally at a higher price compared to scheduled transactions cost. It is evident that improvement in load forecast has a direct positive impact on system security and also cost of operation [1]. Locational-pricing method, take into account use-of-system charges and connection charges [4]. Other methods use price-prediction filters to achieve both lesser cost and better peak-to-average ratio [1]. In this approach, short term load forecasting has been adopted to improve the energy efficiency without compromising with consumer's household demand. An hourly peak consumption pattern for the next day is predicted using artificial neural network (ANN) prediction technique [8]. The predicted load profile along with cost function is displayed on the user network. Scheduling is then done for area-load based cost function using ACO and hence a comparatively smoother load profile is obtained. This provides freedom and flexibility to each consumer to shift high power household appliances in accordance to the displayed load profile. The consumer's actual energy usage profile would then be used in evaluating the corresponding individual load factor (LF), thus encouraging to adopt load shifting strategy in order to reduce the daily electricity bill by furnishing suitable rebate. This would in return benefit the generating unit by operating at improved load factor.

## II.SYSTEM MODEL

Load factor of consumer is defined as ratio of average energy consumption over a period to peak energy consumption of consumer in that period. Electrical energy supply cost is largely depended on load factor. Higher the value of load factor lower will be the overall cost per unit generated. The load data taken from the college power house is given in table I.

TABLE I. ACTUAL LOAD DATA

HOUR	POWER in kW				
	MON	TUE	WED	THU	FRI
8 AM	204.3	200.4	210.4	198.6	216.8
9 AM	422.6	410.5	403.3	389.1	456.7
10 AM	430.2	421.1	410.6	404.4	465.8
11 AM	443.9	390.8	406.2	447.8	456.1
12 PM	379.8	378.9	380.2	407.0	488.6
1 PM	380.4	380.7	384.5	374.9	398.2
2 PM	446.2	417.2	356.7	461.6	446
3 PM	392.4	459.3	425.4	342.7	451.2
4 PM	326.6	450.8	384.4	287.3	274.4

From the load data, the load factor can be calculated based on the following formula.

$$\text{Average Consumption} = \frac{\sum_{i=1}^N \sum_{h=1}^T (w_i^h) * t_h}{\sum_{j=1}^T t_j} \quad (1)$$

$$\text{Load Factor} = \frac{\text{Average Consumption}}{E_{\max}} \quad (2)$$

Here  $w_i^h$  = load of the ith device in  
hth time interval

$t_h$  = hth time interval

No of device = 13

Time interval = 1 hour

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By applying equations 1 and 2, average consumption and load factor can be calculated. Therefore the average consumption of the 13 device in 1 hour time interval is 19.1 kW and the corresponding load factor is 32% between (12-1 PM). The average consumption and the load factor for every one hour time interval is described here. Average consumption is 47.7 kW and the load factor is 23% (1-2 PM), average consumption is 18.2 kW and the load factor is 42% (2-3 PM), average consumption is 8.45 kW and load factor is 35% (3-4 PM), average consumption is 11.88 kW and load factor is 44% (4-5 PM), average consumption is 5.05 kW and load factor is 19% (5-6 PM), average consumption is 5.49 kW and load factor is 26% (6-7 PM), average consumption is 2.53 kW and load factor is 29% (7-8 PM), average consumption is 3.51 kW and load factor is 21% (8-9 PM), average consumption is 1.05 kW and load factor is 19% (9-10 PM), average consumption is 0.81 kW and load factor is 16% (10-11 PM), average consumption is 0.47 kW and load factor is 11% (11PM-12 AM), average consumption is 0.50 kW and load factor is 11% (12-1 AM). From the above data, it is observed that the maximum load factor is 44% at 5 PM and minimum load factor is 11% at 1 AM.

### III.LOAD PREDICTION USING ARTIFICIAL NEURAL NETWORK

For area-load based pricing the actual load of area is required by consumers for scheduling their devices. Among all artificial intelligence (AI) techniques neural network is the most suitable for pattern recognition. A back-propagation neural network is used with one hidden layer for short-term load forecasting required for the present study. The details of network used for prediction are as follows and the neural network architecture is given in figure1.

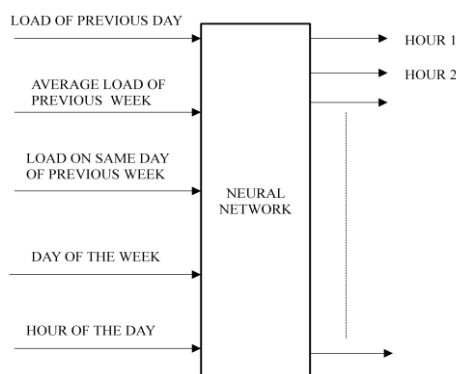


Fig. 1. ANN Schematic Diagram

#### A. Input Parameters

The load data of 24 hours is given as an input to the NN.

#### B. Input Layer

In this system, n=2 is taken as input.

Input 1= week selection, 1-3 (Three weeks are considered)

- 1-First week
- 2- second week
- 3- Third week

Input 2= Day selection, 1-7

- 1- Monday
- 2- Tuesday
- 3- Wednesday
- 4- Thursday
- 5- Friday
- 6- Saturday
- 7- Sunday

#### C. Hidden Layer

The output of the input layer is used as input of hidden layer. In this, the activation function used is tan-sigmoidal.

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## D. Output Layer

The outputs of hidden layer are used as inputs for this layer. The activation function used is linear-sigmoidal. The NN is trained by actual load data and it has predicted the load for the future weeks. Here, it is trained with three weeks data and the predicted data is given in table II.

TABLE II. PREDICTED LOAD DATA

HOUR	POWER in kW( MONDAY)		
	Prediction for I week	Prediction for II week	Prediction for III week
8 AM	214.24	232.37	256.59
9 AM	405.32	451.62	404.59
10 AM	425.8	444.07	439.211
11 AM	443.13	380.36	368.89
12 PM	383.78	353.611	336.4
1 PM	380.93	448.04	292.89
2 PM	464.11	329.18	430.82
3 PM	380.93	290.45	367.13
4 PM	318.64	258.94	274.2

## IV.RESULTS AND DISCUSSION

The neural network is an important intelligent technique which is applied for pattern recognition. The neural network's exhibit mapping capabilities, that is, they can map input patterns with the associated output patterns. Here, 24 hours load data is taken for three weeks. In order to manage the load demand at the peak hours and to shape the load curve, prediction of the load for the future is important. The actual load data is given to the neural network and it is trained and it will predict the future demand. The results obtained are the actual load curve for Monday and predicted load curve for Monday and it is given in Fig 2 and Fig 3. The performance plot for neural network training is shown in Fig 4 and the regression plot between network response and target is shown in Fig 5. By giving the actual load data to the neural network as an input and it is trained and it will predict the future loads. Fig 3 represents the predicted load curve for Monday. The neural network has predict the load for fourth, fifth and sixth week. Fig 4 shows the performance curve and it depicts that the neural network has achieved the goal at  $10^2$  with 1000 epochs.

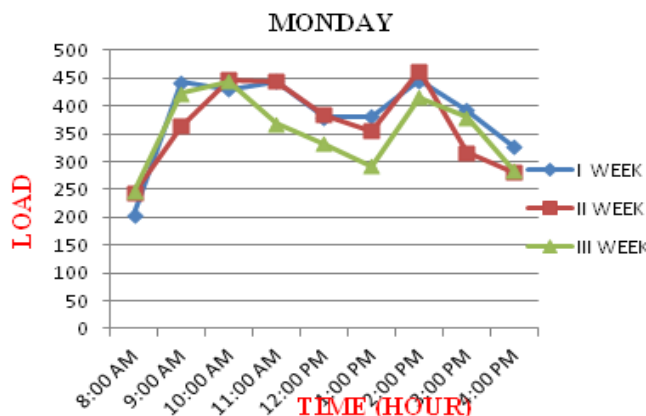


Fig. 2. Actual Load Curve for Monday

The blue line represents the consumption of load for first week of Monday from 8'o clock to 4'o clock and the red line represents the consumption pattern for second week of Monday and green shows the load consumption for third week of Monday. This curve indicates that the maximum energy consumption is 450 kW at 2'o clock. The predicted curve is given in figure3.

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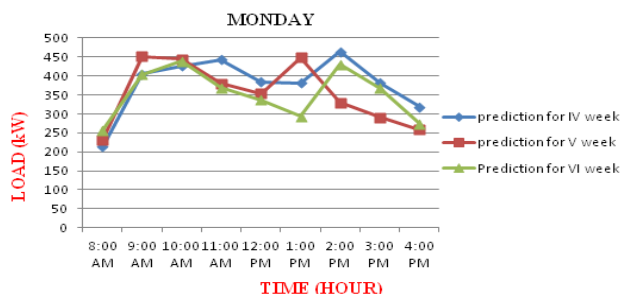


Fig. 3. Predicted Load Curve for Monday

The neural network has predict the load for fourth, fifth and sixth week. The blue line represents the consumption of load for first week of Monday from 8'o clock to 4'o clock and the red line represents the consumption pattern for second week of Monday and green shows the load consumption for third week of Monday. This curve indicates that the maximum energy consumption is 450 kW at 2'o clock. The predicted curve is given in figure3.

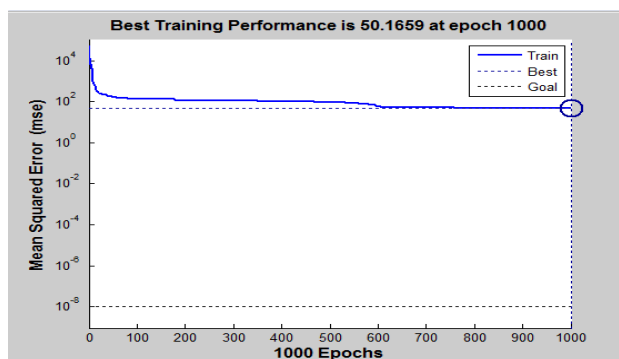


Fig. 4. Performance curve for NN training

The performance curve for neural network training is given in fig 4. The best training is attained at 50 epochs. This plot shows that the neural network has attained its best at  $10^2$ .

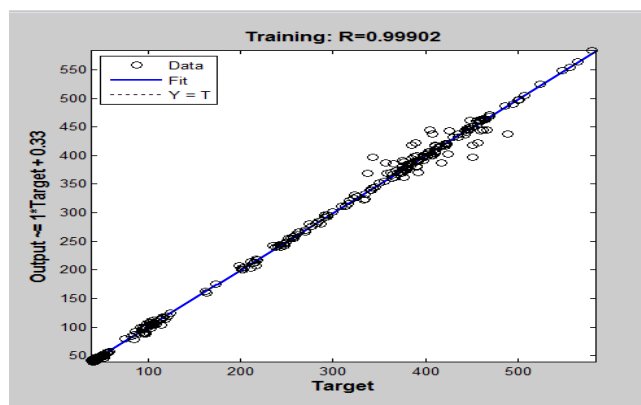


Fig. 5. Regression plot

The regression plot is shown in fig 5. The prediction can be done with the training of data and the target is achieved at 0.99 .



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## V.CONCLUSION

Demand Side Management (DSM) is a portfolio of measures to improve the energy system at the side of consumption. It ranges from improving energy efficiency by using better materials, over smart energy tariffs with incentives for certain consumption patterns. By charging users more in peak and less in off-peak hours, the provider can induce users to shift their consumption to off-peak periods, thus relieving stress on the power grid and the cost incurred from large peak loads. Here, Short term load forecasting has been adopted to improve the energy efficiency without compromising with consumer's demand. The peak consumption for the next day is predicted by using neural network. The neural network is trained by actual load data and it has predicted the hourly consumption pattern for the next day.

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