ТЕХНІЧНІ НАУКИ

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SHORT-TERM LOAD FORECASTING USING MILTI LINER REGRESSION BASED ON ARTIFICIAL NEURAL NETWORK

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Load forecasting is a important tool for the energy industry, as it can influence areas like power generation and trading, infrastructure planning, etc. The implementation of the load forecasting tool in distribution networks has a wider impact up to the level of electricity generation. Load forecasting has been an area of energy systems, where human experts still perform better than the algorithms which were put forward as alternatives. Many techniques have been put forward for the accurate load forecasting. Different Artificial Neural Networks (ANN) with different architectures have been proposed in the last few years for load forecasting purpose resulting in a large number of publications on this subject. In this paper, we propose a New Neural network direct power supply for short-term load forecasting depending on the weather changes for systems of distribution management. The proposed neural network can predict the load profile with a run time of one to seven days.

Keywords: short term load forecasting, multi liner regression, artificial neural networks, weather sensitive load forecast.

Introduction. The electricity industry is in a developing phase in which the achievements that have taken place in information technology (IT) are included to make the generation, transmission and distribution of electricity scenario works in an efficient way both from the point of view of cost and from the point of view of energy. Availability Based Tariff (ABT) concerns itself with the tariff structure for bulk power and is aimed at bringing about more responsibility and accountability in power generation and consumption through a scheme of incentives and disincentives. In an earlier scenario, the generating utilities used to generate as much as they could generate, and the transmitting companies distribute it to the distribution companies. As the power supply is such that it cannot store it in a large part for the longer duration, this mode of operation is completely inefficient. In the new scenario, the generating stations generate only the capacity required for optimal humidification of the coordination and commitment of the power units. This forces utilities and distribution companies to forecast their demand for load and give the same to generating stations. The incentives and disincentives force them to show the exact load requirements of the generating stations.

Business drivers for downsized distribution utilities are profitability combined with improved end-customer service. In General, distribution networks buy electricity from transmitting companies and bear the main responsibility for its delivery to consumers. The distribution company is obliged to provide uninterrupted customer service with sufficient capacity to meet the needs of consumers. If the distribution company does not have sufficient capacity to meet customer requirements, this can lead to problems that may occur due to overloading. Overloading the system can cause partial or pony destruction of the distribution system. To overcome the situation, they may be forced to consume more electricity from the transmitting company than they agreed to buy, which in turn can pay for the stability of the transmission network itself.

Load Forecasting. Depending on the forecasting period, there are three types of load forecasting, namely short-term load forecasting (STLF), which, as a rule, the period varies from one hour to one week, medium-term load forecasting which is usually for a period ranging from one week to one year and long-term load forecasting, which is during the period exceeding one year. Of these, long-term forecasts are used when planning infrastructure development. Short-term forecast of the load on the objects affected by the short-term, such as the production and sale of energy.

The demand load varies with weather changes. Short term load forecasts can help to estimate the load demand according to the changes in the weather conditions and this information can be used to increase the system reliability and economic operation. The short term load forecast founds a variety of applications such as unit commitment, economic dispatch, hydrothermal co-ordination etc. Over-prediction causes increase in operating costs by unnecessary use of reserves, while under-prediction results in failure of meeting demand which could have met easily with the reserves. Various methods have been proposed for short-term load forecasting. There are traditional methods and non-traditional methods. The main conventional techniques that are in use are the similar day approach, the regression analysis and the time series analysis. In the similar day approach the historical load data of the previous one or two years is searched for a similar day in terms of day of the week, weather and date. This method most often fails as it can be difficult to find a similar day. In time series analysis, historical load is treated as time series data, and future data is predicted using the extrapolation method. There is a high probability that the extrapolation method fails due to different weather conditions or due to some random events that may occur. The regression analysis method tries to find the relationship between the input and output variables. Once the relation is identified the outputs for a given input set can be easily calculated. But finding an exact mathematical relationship is difficult and because of this reason this method also fails many a time. According to Kolmogorov theorem neural networks can approximate any non linear continuous function with a good precision. Because of this feature the artificial neural networks are extensively used in areas like prediction, system modeling and control. One of the examples for the application of ANN for prediction is STLF.

Load data analysis. Electrical load is a combination of different components as shown in the equation (1). Load = $L_{normal} + L_{weather} + L_{special} + L_{random}$.

Each day of the week has a specific load model.This component is represented by L_{normal}. Every Sunday has a common base template, every Monday has a different base template and so on. Usually on weekends the power consumption is much less than on weekdays. Monday and Friday have different load pattern from other weekdays as they are closer to weekends. There is a component of load which depends on the weather denoted by $L_{weather}$. In winter the power consumption is high in residential areas because of increased use of heaters and in summers due to the increased use of coolers. The weather parameters which affect the load are temperature, humidity, rainfall and wind. The effect of these weather parameters is different depending on the type of consumers and the geographical features of the area under consideration.

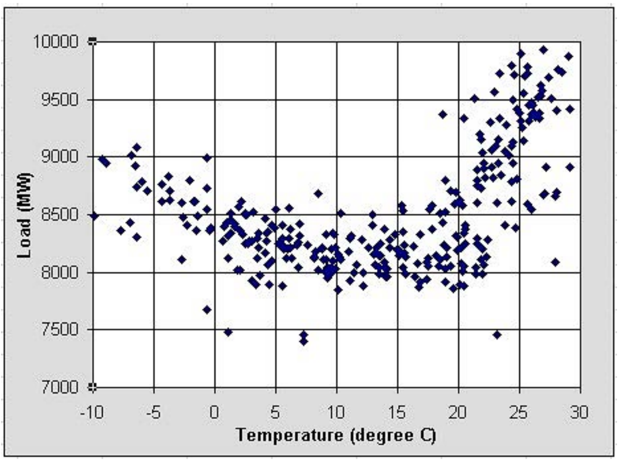

Fig. 1. Load – Temperature scatter diagram

There are several special occasions, such as Seasons festival, elections, major sporting events, etc., which in turn will cause changes in the load structure. This corresponds to the $L_{special}$. There are some random factors which affect load and this load component is L_{random}. Load and weather variables were analyzed for any correlation between them. Figure 1 shows the temperature load scattering Diagram. From the analysis of electrical load and temperature were strong parabolic. Other weather variables such as humidity, precipitation, wind, etc., were found to have very week relation to the load, and therefore they were not considered in the forecasting procedure.

Artificial Neural Network (ANN). Neural networks are modeled like the human brain. The main building blocks are known as neurons. In each neuron, the inputs coming into it are combined, and that amount is then transmitted through the activation function, which is the transfer function of the neuron. A neural network is a network formed by neurons, and the weights that connect these neurons form the memory of the network. The General architecture is shown in figure 2. The process by which a neural network is configured to run a specific application is called learning. The nearby learning network is similar to the process of teaching people. Once the network is trained with different patterns of input and output combinations ideally, it should be able to predict the correct output when the input pattern is given randomly. The most commonly used learning algorithm is back-propagation algorithm with the gradient descent algorithm.

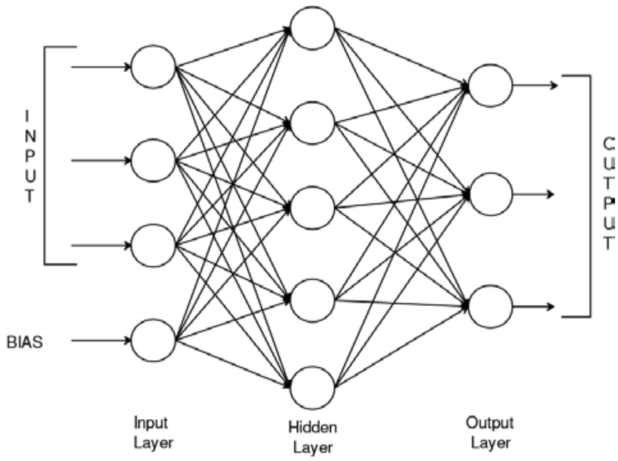

Fig. 2. Artificial neural network

Typically, the network has three or more layers of neurons. Inputs directly to the input layer. The network output can be derived from the output layer. Typically, only one hidden layer is used, and in some cases, two zero layers are also used. The number of neurons in the zero layers is also a factor to consider. According to the Kolmogorov theorem the network should have one neuron extra than double the number of neurons in the input layer. But usually the numbers of hidden layer neurons are found out by hit and trial method. Genetic Algorithm (GA) can be utilized for hidden neural network architecture optimization. But it can be really timeconsuming as training of the network also has to be done in each of the iterations. Despite the fact that the performance of neural networks depends on the parameters of the network architecture, such as hidden layers, hidden layer neurons and activation functions used in the network, the choice of the input parameters holds the key to get the best performance from the network. The network structure selected here is having 31 inputs, one hidden layer and one output layer with 24 neurons. Only one hidden layer is selected. In the output layer the load forecast for the each hour of the day is obtained from each neuron in the output layer. Historical load and temperature form the main parts of the input to the network and the rest are temperature forecasts and information of the day of which the network is going to predict the load.

Details about the 31 inputs and the 24 outputs of the network are shown below in Table 1.

Table 1

ANN inputs and outputs

Inputs	Description
1-24	L(d-7, h); h = 1 to 24
25-27	Tmax(d-7), Tmin(d-7), Tavg(d-7)
28-30	Tmax(d), Tmin(d), Tavg(d)
31	Day Type
Outputs	**Description**
1-24	L(d, h); h = 1 to 24

Note: L — Load; Tmax — Maximum temperature; Tmin — Minimum temperature; Tavg — Average temperature; d — The current day; h — Hour of the day.

Scaling of input and output variables was done to prevent saturation of neuronal outputs. The network Output was then reduced to the original range by performing a reverse process to obtain the predicted loads in the actual range. The network was trained with one-year data using a back propagation algorithm. After the network training was completed, weights and offset terms were kept fixed for the current year. The network is configured for automatic annual training to match periodic load increases. Like the 24-hour forecast, week-ahead forecasts are also necessary for a single commitment, hydrothermal coordination and transaction evaluation. The weekly prediction model provides this capability. Added to form 6 additional daily load forecasting networks a week ahead load forecasting model with each network forecasting for each of the next 7 days. As the same network is used the same accuracy is assured for weekly forecast as well.

Results. The network was trained with data comprising of loads and corresponding temperatures for 365 days using a back-propagation algorithm. After completion of training, the network was tested with data including loads and corresponding temperatures of 122 days. The accuracy of the result was calculated using the Mean Absolute Percentage Error (MAPE)s calculated using the equation (2).

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\frac{Actual\,i - Forecasted\,i}{Actual\,i}100$$

MAPE, obtained after testing the network with four months of load and temperature data, was 2.33%. Figure 3 shows the results of the forecast for one week.

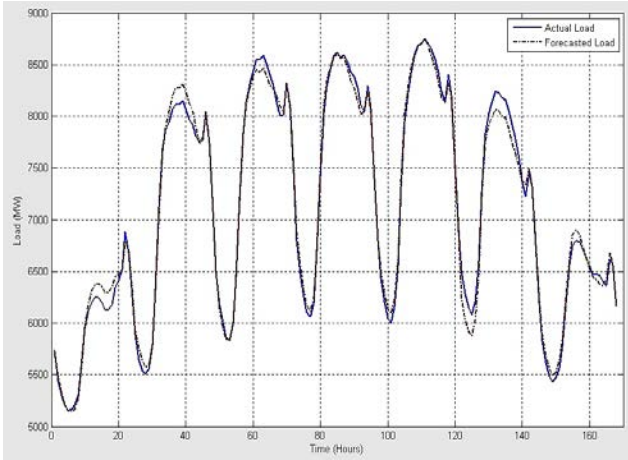

Fig. 3. One-week load forecast

Conclusion. With the introduction of an affordable tariff, distribution companies will be forced to buy electricity from transmitting companies in an optimal way with less than 4% consumption due to incentives and constraints associated with ABT. This in turn forces the end customer to use the power in the optimal way because of the high cost for power at peak hours. The use of short-term load forecasts by distribution companies helps them buy electricity from transmission utility in an optimal way there by improving their distribution network reliability and customer service. A short-term load forecasting method based on ANN was proposed, based on weather changes for use in distribution networks. The network has two modes of operation, the Mode of the forecast for the next day and the mode of the forecast for next week, both provide hourly load forecasts. An important parameter in this load prediction is the weather forecast. Since the weather variable that is considered for this network is temperature and temperature forecasts are readily available, network inputs are readily available to distribution networks. Test results shows that the network is able to forecast the load with sufficient accuracy which helps in better planning.

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КОРОТКОСТРОКОВЕ ПРОГНОЗУВАННЯ НАВАНТАЖЕННЯ З ВИКОРИСТАННЯМ МУЛЬТИЛІНІЙНОЇ РЕГРЕСІЇ НА ОСНОВІ ШТУЧНОЇ НЕЙРОННОЇ МЕРЕЖІ

Анотація
Прогнозування навантаження є вкрай важливим інструментом для електроенергетики, оскільки може впливати на такі галузі, як виробництво електроенергії і торгівля нею, планування розвитку інфраструктури і т. д. Реалізація інструменту прогнозування навантаження в розподільних мережах надає більш широкий вплив аж до рівня вироблення електроенергії. Прогнозування навантаження було областю в енергетичних системах, де людські експерти все ще працюють краще, ніж алгоритми, які були висунуті в якості альтернатив. Багато методів було висунуто для точного прогнозування навантаження. В останні кілька років для цілей прогнозування навантаження були запропоновані різні штучні нейронні мережі (ANN) з різними архітектурами, що призвело до великої кількості публікацій по цій темі. В даній роботі запропонована Нова Нейронна мережа прямого живлення для короткострокового прогнозування навантаження в залежності від змін погоди, для систем керування розподілом. Запропонована нейронна мережа може прогнозувати профіль навантаження з часом виконання від одного до семи днів.
Ключові слова: короткострокове прогнозування навантажень, мульти-лінійна регресія, штучні нейронні мережі, навантаження чутливе до погодних умов.

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КРАТКОСРОЧНОЕ ПРОГНОЗИРОВАНИЕ НАГРУЗКИ С ИСПОЛЬЗОВАНИЕМ МУЛЬТИЛЕНЕЙНОЙ РЕГРЕССИИ НА ОСНОВЕ ИСКУССТВЕННОЙ НЕЙРОННОЙ СЕТИ

Аннотация
Прогнозирование нагрузки является крайне важным инструментом для электроэнергетики, поскольку может влиять на такие области, как производство электроэнергии и торговля ею, планирование развития инфраструктуры и т. д. Реализация инструмента прогнозирования нагрузки в распределительных сетях оказывает более широкое влияние вплоть до уровня выработки электроэнергии. Прогнозирование нагрузки было областью в энергетических системах, где человеческие эксперты все еще работают лучше, чем алгоритмы, которые были выдвинуты в качестве альтернатив. Много методов было выдвинуто для точного прогнозирования нагрузки. В последние несколько лет для целей прогнозирования нагрузки были предложены различные искусственные нейронные сети (ANN) с различными архитектурами, что привело к большому количеству публикаций по этой теме. В данной работе предложена Новая Нейронная сеть прямого питания для краткосрочного прогнозирования нагрузки в зависимости от изменений погоды, для систем управления распределением. Предложенная нейронная сеть может прогнозировать профиль нагрузки с временем выполнения от одного до семи дней.
Ключевые слова: краткосрочное прогнозирование нагрузки, мультилинейная регрессия, искусственные нейронные сети, нагрузка чувствительная к погодным условиям.