Cloud-based Long Term Electricity Demand Forecasting using Artificial Neuro-Fuzzy and Neural Networks

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Abstract

The supply-demand equilibrium is the main criteria for determination of electricity pricing for both electrical power production companies and ordinary (household) users. The companies must be sure about future demands of electricity for uninterrupted efficient electrical supply. The demand of electricity is affected from weather conditions, process of economy, working and nonworking days of a year, etc. Therefore, forecasting demand by using current and historical data is very important for electricity trading and producing companies. In this study, a cloud-based forecasting service which is based on neural network model is proposed for long-term electricity demand forecasting of Turkey. Cloud based nature of the proposed system help continuous training and improved forecasting capability over time from the system. Following year overall electric demand is approximately estimated with neural network and artificial neuro-fuzzy inference systems.

1. Introduction

Accurate electricity price and demand forecasting models have great importance for electricity trading and producing companies, since they decide on their purchase/produce rates, based on production load, and invest in new electricity production/distribution infrastructures. The load forecasting is much complex than price forecasting [2] because the demand depends on not only the category of electricity users, but also the economic and physical constraints like weather, humidity, cloudiness, and temperature [3]. Demand forecasting can be categorized as [4]: Short term forecasting [5], Mid-term forecasting, and long-term forecasting. In short term, the foresighted data is limited from one hour to one week. Short term forecasting is important for companies to tender a price. Similarly, for mid-term forecasting is a time frame from one week to one month, and, long-term forecasting is more than and equal to one year. The delay at the historical data needed for forecasting becomes increased as the time domain of forecasting increases. As an example of hourly forecasting problem, for short term forecasting (i.e. 24 hour forecasting), the information or database is ready for 1 hour ago (1 data for samples are taken per hour) at minimum and 1 day ago (24 samples) at most, but for long-term forecasting, the time interval is almost one year, which means the time intervals increases to 365 days ago (almost 9000 samples).

Long term demand forecasting is relatively harder engineering problem when compared to short term forecasting problem since it is always inaccurate because estimation error for all economical and weather parameters is higher when compared with short term data [6], so necessity for long term accurate weather and economical data isn't available. Another important property is that as the delay between input and output (forecasted) data increases, the forecasting becomes more problem dependent [7] because for each country economical parameters, population concentration, seasonal non-working days, preferred energy sources for heating and cooling differs from each other. In this study, a long-term demand forecasting for Turkey electricity market was investigated. Even the economical factors plays important role for long term forecasting, Historical data of demand and weather conditions from Jan. 2010 to Jan 2014 are evaluated for training and testing feed forward neural network without using economical factors like population workday and nonworking days due to their direct effect on electricity demand. Therefore, the purpose of neural network is to estimate the next year's demand for a given hour of date with a relatively small number of inputs without delay. Therefore, as a part of this study, the number of inputs, frequency of historical data and physical inputs with the number of neurons on hidden layers was investigated.

2. Literature Review

There are many papers published in last 30 years since the demand and price forecasting at electricity price market is critical for the mentioned reasons. In the longest time period, also review papers have been published and some of them gave the overall information and comparison among previous published paper. In this section, a general framework of this study was established. For this purpose, first the short term neural network forecasting studies are investigated with respect to the number of inputs and preferred models. Next, with the aid of relationship between obtained results and models, the long term forecasting papers were evaluated. By the reason of an investment on distribution or generation of electricity needs years, the long-term forecasting problem is crucial for electricity-related companies. Instead of next day's or next week's electricity demands, next year's electricity demands are desired for this problem. The first review paper can be found in 1983 [8] and 1987 [9]. These papers gave critical survey of probabilistic exponential and polynomial models, and reported the need of demographic and economical factors.

In 90s, the soft computing methods were applied to the problem. In [10], genetic programming model were applied to the problem. Instead of weather data, economical data; population, GDP, and electrical demand of Korea are preferred as independent input. In [11] authors preferred delayed historical load data and compared different delay times as cases. After 2000, studies more focused on neural network in the light of short term forecasting performance. In [12], authors forecasted 20 year load data by using neural network. The authors use many different data sets as input such as GNP, GDP, number of households, number of air conditioners, amount of CO2 pollution, industrial production, oil price, and amount of energy consumption, electricity price and average temperature. As one of the important result of this paper that both temperature and economical data are preferred as inputs of neural networks. In [13], only historical load data are evaluated. After 2005, the researchers are more focused on economical data for long term forecasting [7, 14-18]. In this part, it has observed from previous papers that;

- Long term forecasting is inaccurate
- Hourly demand is affected from temperature
- Long term forecasting becomes increasingly case depended. Hence, isn't possible to compare performances of different countries.
- Demographical and economical factors has influence on performance

Since the number of long term forecasting papers is relatively small in number when compared too short term forecasting, more study needs for this problem. Therefore, in this study only historical temperature and load data are selected as inputs on this paper. This paper is organized as six sections. Section 3 gives a short introduction of neural network, and Section 4 is for explaining the experimental setups which are compared in this paper. In this section different case of neural networks are designed and the performance of each case is compared with respect to mean average of percentage error (MAPE %), and conclusion is given in Sections 8.

3. Fundamentals of Forecasting Algorithms

In this paper, two important soft-computations based forecasting methods which are neural-network and neuro-fuzzy systems are evaluated to forecasting the one year later electricity demand from Turkey's electric demand and temperature data. In this section, these two computational tools are briefly discussed.

3.1. Neural Network

In general, neural networks can be regarded as parallel connected groups of mathematical processing units with adjustable weighted connections. Neural networks can learn from data, approximate (non)linear function (also learning), and they are robust against noisy inputs. The neural networks (NNs) have one directional signal flows from input to the output. Feedforward neural networks are preferred for solving nonlinear classification and regression tasks by learning from data. Hence, due to these properties, in this study feedforward networks are preferred for demand forecasting. Figure 1 presents the structure of feedforward neural network.

The NNs are organized as layers (Figure 1 presents two hidden layers). Each layer has a specific number of neurons, which are main processing units of NN, sums all inputs with a bias and applied to a function called activation function. Eq.s (1) and (2) present the mathematical operator for each of neurons.

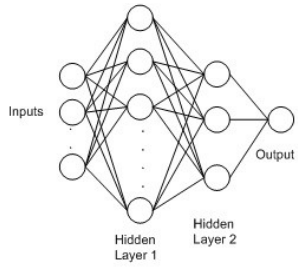

Fig. 1. Pictorial description of feedforward neural network.

$$o = \sum_{i=1}^{n} x_i w_i + w_{n+1} \tag{1}$$

$$y = f(o) = \frac{1}{1 + e^{-\lambda o}} \tag{2}$$

where n is the number of inputs to a neuron, w_i are the weights of connections, w_{n+1} is the bias, f is the activation function (sigmoid function is given for an example and used in this study), and y is the output of neuron. The NNs has input and output layers, between them many hidden layers can be defined. Since the input and output layers have constant connection, there could be any configuration defined for hidden layers. In this study, many possible single and double layered configurations have considered and compared. In this study, historical demand data, temperature, date and hour of a day are taken as inputs with no delay. The output of NN is the demand of the given date and hour. Therefore for forecasting a years all demand data, the system should run 24x365 times. Instead of application based software, the proposed method is planned to distribute on web environment. Hence, in the next section, the cloud environment for proposed NN system was explained.

3.2. Artificial Neuro-Fuzzy Inference System (ANFIS)

Artificial Neuro-Fuzzy Inference System (ANFIS) [19] is a network system with Sugeno fuzzy modules connected to each other as graphically demonstrated in figure 2, as given the figure, the system has five layers. The first layer is the section for applying the inputs to the following membership functions. For this example and for implementation each input is assigned to two bell membership functions. The outputs of layer 1 are multiplied with each other at layer 2, and this new value becomes the weight of the next layer. In layer 3, all weights (firing strength) are normalized, set to the interval [0,1]. In layer 4 consequent parameters are determined with respect to the formed rules. In the final layer the output is formed with the sum of the previous input data. The detailed information about implementation and formulation can read in [19].

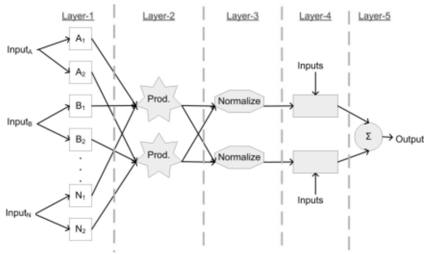

Fig. 2. Graphical demonstration of artificial neuro-fuzzy inference system.

4. Cloud Environment

Service oriented architecture (SOA) for software is a relatively new approach for development and deployment of software products. There have been reference architectures defined by big companies like IBM, Microsoft and Oracle which indicates that the trend in software development and deployment has shifted towards SOA. Reference research papers [20,21] provide an overview of the architecture and how software is designed/deployed as a service. Services defined in this context provide a well-defined definition of expectation from a software product. Separation of concern achieved through "software as a service (SaaS)" approach helps developing customer friendly service interfaces which remains unchanged even if there are regular modifications/updates applied to the back-end software product. In the context of this paper Neural Network based prediction algorithms are implemented in the back-end and hidden from customers, users of the forecasting service. This allows developers to switch algorithms seamlessly in order to provide the most accurate forecast. By separating the service definition and the back-end processes for forecasting we have enabled a way of tailoring user oriented definition of forecasting services. Users are also given the option of improving the outcomes of forecasting by prioritizing the parameters to be used for forecasting. Parameter selections are translated to the back-end as small alterations in the training and classification processes executed in the forecasting engine. Service oriented architecture proposed here enables users of the systems (mainly electricity resellers, to tune the system based on their own experience in order to differentiate themselves from other competitors. Parameter selections for estimation and alterations made to the training parameters are logged and monitored over the time. Best working approach will be integrated to the main training cycle over the time. Cloud based approach, unlike proprietary software systems, helps us train a universal demand estimator as the system will learn and adapt to new data and/or situations. As a result, the demand estimation sub-system will generate more accurate estimations over the time and will also adapt to new situations that can be observed by regular feedbacks from both users and real-time data feeds.

5. Experimental Setup and Results

In this study, two different forecasting methods are applied on the historical data of electricity demand and temperature. Firstly, long term demand forecasting was proposed for different hidden layer configurations of neural network. As input, the database of historical data (1 year ago) of demand, maximum, minimum and average of temperature were considered for training and testing the proposed model. The data was taken from Jan 2010 to 1 Jan 2014. Hence the historical data of 2010-2012 is considered for training phase. In this study only 7 inputs are selected, which are date, demand data of previous year, maximum, minimum and average temperature of previous year without any time delay. Table 1 presents the MAPE value for different Neural Network configurations.

Table 1. Single and double hidden layered feedforward neural network performance comparison.

Layer 1	Layer 2	MAPE (%)	Layer 1	Layer 2	MAPE (%)
5	-	13.77	10	15	13.38
10	-	17.99	10	20	17.01
15	-	72.25	15	5	10.58
20	-	11.2	15	10	15.69
5	5	17.48	15	15	11.75
5	10	15.23	15	20	36.42
5	15	18.5	20	5	41.20
5	20	20.3	20	10	20.11
10	5	13.17	20	15	22.10
10	10	36.82	20	20	23.52

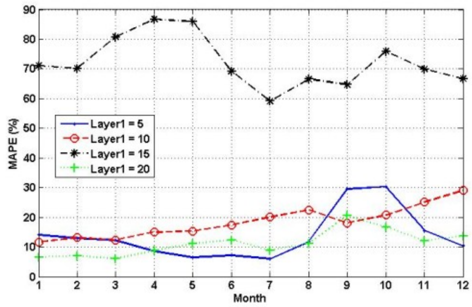

Fig. 3. Graphics for single hidden layer performance.

The results which are showed in Table 1 can be divided into two categories based on the number of hidden layer. The performance of single layer network is graphically demonstrated in Figure 3, and it is concluded that for single layered problem the number of neurons n hidden layer 5 and 10 are almost similar to each other. Hence, there is not a direct relation between number of neurons and performance of trained neural network. The results obtained in this section indicates that an empirical study should be evaluated for best network configuration and from previous studies, only two layered NN's performance was successfully applied to the both short and long term forecasting problems. Even the best choice is 20 neurons for single layer. Double hidden layered neural network configurations have also evaluated, and have added to Table 1. From all configurations that are given in Table 1, the double hidden layered with [15 5] neurons for each layer respectively have presented best performance and MAPE reduced to 10.58%. The performance of best configuration per month is graphically presented in Figure 4. From Figure 4, the MAPE value per month can observe. From the month is can be concluded that month 3 has the lower MAPE value. Therefore, to present the performance of the proposed structure, the forecasted and actual demand of September and March is given in Figures 5 and 6 respectively. When the test data was investigated, it was seen that for all 4 years, demand data has same frequency with different amplitudes for March demand data. Therefore, it isn't surprising that March has the lowest MAPE value. On the contrary, both September and October has the biggest MAPE value. The reason is depended on differences on both historical demand and temperature data. Like September, October also has large difference between demand data; however temperature is more similar in years than September.

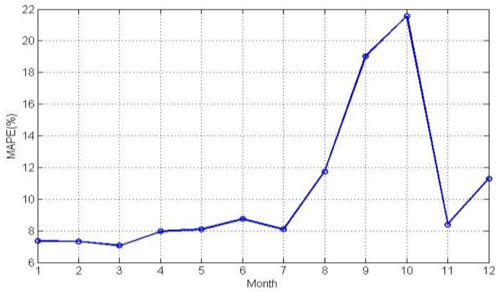

Fig. 4. Graphics for single hidden layer performance

This result also indicates that when compared to demand data temperature data has smaller effect than demand data for long term forecasting. Figure 5 gives the difference and complexity of the problem for September. Between data 300 and 500, an unexpected decrease at demand can be observed. In the case of learning of the algorithm, the relatively rapid change at demand cannot be followed. Therefore in Figure 5, the forecasted demand just follow almost the same average amplitude, the forecasted data could not able to track the actual data. Figure 6 gives the best fitting of forecasted data and actual demand data. The forecasted signal follows the same period of change with a small error at the amplitude. However, at the end of month, the error increases since the demand was decreased. Also the common conclusion from both Figures 11 and 6 is that at the end of week, the error between predicted data and actual data in increased. Secondly, the same data set is applied to ANFIS system.

The overall MAPE is reached to 9.5811, which is lower than neural network performance. Similarly, figure 7 is given for the worst performance month for the ANFIS system respectively. The MAPE error per month is presented in figure 8. The MAPE difference per month graphic for both algorithms has almost same pattern such that for September the largest error is reach for two algorithms.

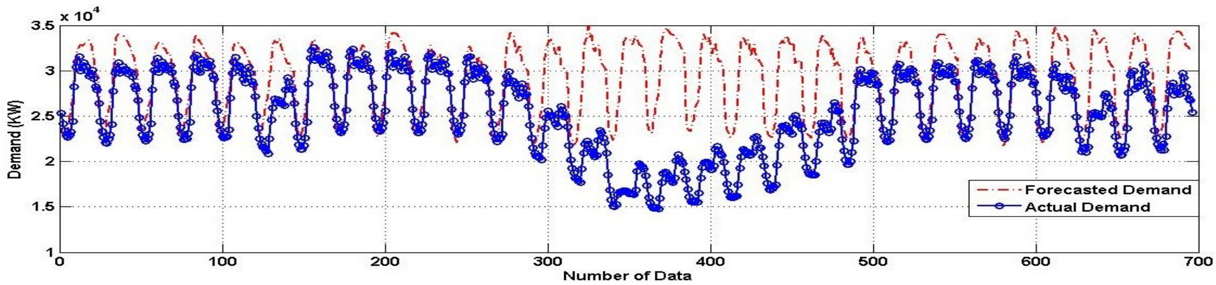

Fig. 5. Forecasted (Neural Network) and actual demand data for September 2013.

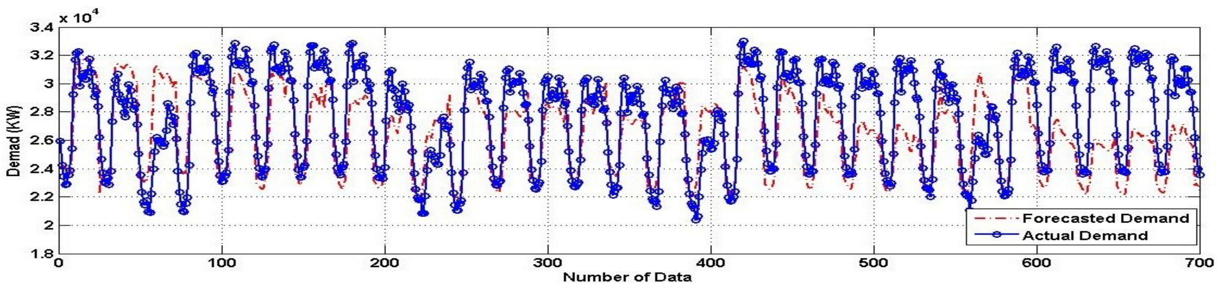

Fig. 6. Forecasted (Neural Network) and actual demand data for March 2013.

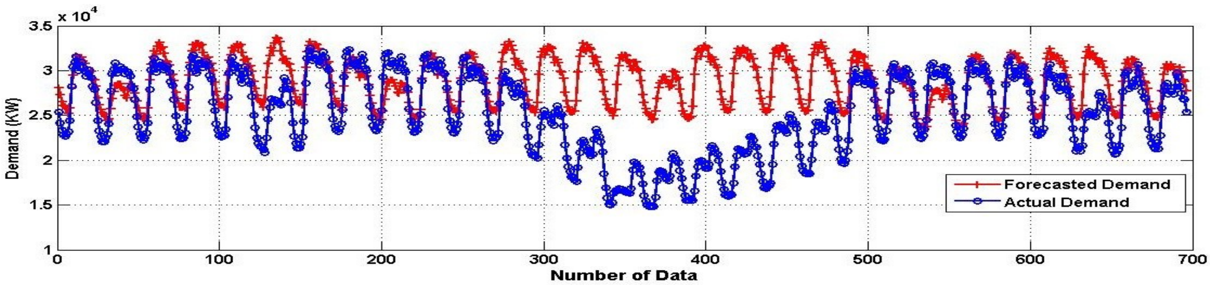

Fig. 7. Forecasted (ANFIS) and actual demand data for September 2013.

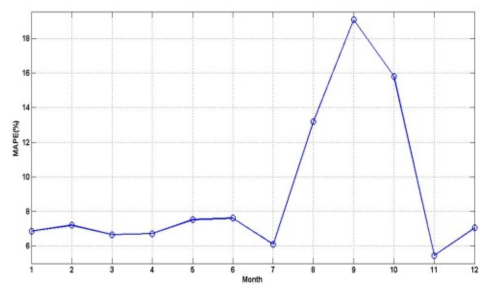

Fig. 8. Graphic for the ANFIS performance.

6. Conclusions

In this study, single and double hidden layered feedforward neural network structures were proposed for long term forecasting of electricity demand by using only historical temperature and demand data. These structures differ from each other with respect to the complexity of neural network. The results show that the performance of system does not depend on the complexity and number of neurons in hidden layers of the system. The idea of using average temperature data allows the forecasted data to track the sinusoidal change in the demand. Also the best improvement was obtained as 7.075%, and 10.58% in average for whole year. Same study is repeated with ANFIS algorithm. Best improvement with ANFIS was obtained as 6.104%, and 9.1153% in average for whole year. The results show that ANFIS is a better tool for long term forecasting. As future study, augmenting the dataset with humidity and weekend indication is likely to improve the performance of the system. Also price forecasting will need to include an important number of attributes from the inputs. As a very important problem, the unexpected change at the demand as given for all September graphics. Although it is possible to track that change with short term forecasting methods, for long term problems it isn't possible since there no indicators. Therefore as future study a decision maker based systematic methodologies will be proposed.

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7. References

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