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Multi Layer Feed Forward Neural Network Model For Gas Load Forecast

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Key Words:
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Abstract: *A multi-layer feed-forward neural network based gas load forecast model for the tell-future load forecast system, is built with Java to show how neural networks work in forecasting is presented in this paper. The multi-layered feed-forward networks performance is well for short-term gas load forecasting. The forecast accuracy has been in excess of 90% for this model. The weather and the calendar information have great impact on the load, especially the temperature. A reasonable number of hidden units for this model is between 7 and 12, and we recommend 10. Performances are not good if the numbers are less than 5 while larger than 12 has no significant decrease in the training error. Learning rate and momentum have significant influence on the training process with the gradient drop method. The gas load depends on many factors such as weather, calendar, and other economic information. The model will capture those effects, reflect them within the system and provide valuable future forecasting data.*

1.Introduction

Load Forecasting is very much important to the operation of electricity companies. It enhances the energy efficient and consistent operation of power system. Artificial neural networks have long been established as exact non-linear mapper. ANN models generally use Back propagation algorithm which does not come together optimally & requires much longer time for training, which makes it difficult for real-time application. Due to different seasonal and monthly changes in electricity consumption, it is difficult to model it with conventional methods. An Artificial Neural Network (ANN) is an important information processing paradigm that inspires by the way the biological nervous system, such as human brain. Neural Network also consists of processing units (artificial neurons) and connections (weights) between them. The processing units transport incoming information on their outgoing connections to other units. The "electrical" information is simulated with specific values stored in those weights that make these networks have the capacity to learn, memorize and create relationships between large data.

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The important feature of these networks is their adaptive nature where "learning by example" replaces "programming" in solving problems. This feature renders these computational models and interesting in application domains where training data are available. There are many different types of neural networks and they are being used in many fields by several researchers; such as Julien Eynard et al [1] reported the outdoor temperature and thermal power consumption forecasting and focuses on the impact on forecast accuracy of various parameters, related with the discrete wavelet transform, such as both the wavelet order and the decomposition level and the topology of the neural networks used. Mishra, S and Patra, S K [2] proposed a smaller MLPNN trained by genetic algorithm & particle swarm optimization. Beccali, M et al [3] presented an approach based neural networks for the electric energy demand forecasting of a suburban area with a prediction time of 24 h. Azadeh, A et al [4] presented the advantage of ANN methodology through analysis of variance (ANOVA). Wei-Chiang Hong et al [5] investigated on employs genetic algorithm simulated annealing hybrid algorithm (GASA) to choose the suitable parameter combination for a SVR model. The empirical results reveal that the proposed model outperforms the other two models, namely the autoregressive integrated moving average (ARIMA) model and the general regression neural networks (GRNN) model. Benjamin F. Hobbs et al [6] reported the sixteen electric utilities surveyed state that use of ANNs significantly reduced errors in daily electric load forecasts. Sahoo, G, B et al [7] examined an empirical model (artificial neural networks (ANN)), a statistical model (multiple regression analysis (MRA)) and the chaotic non-linear dynamic algorithms (CNDA) to predict the stream water temperature from the available solar radiation and air temperature. Ashu Jain and A, M, Kumar [8] proposed an approach for consists of an overall modeling framework, which is a combination of the conventional and ANN techniques. Julien Eynard et al [9] focused on optimizing the functioning of a multi-energy district boiler, adding to the plant a thermal storage unit and implementing a model-based predictive controller. The proposed short-term forecast method is based on the concept of time series and uses both a wavelet-based multi-resolution analysis and multi-layer artificial neural networks. Azadeh, A et al [10] presented an artificial neural network (ANN) approach for annual electricity consumption in high energy consumption industrial sectors and shown that it is a more precise approach to forecast annual consumption in industries.

The observation from these studies is the most traditional applications include are classified as (a) Classificationto determine military operations from satellite photographs; to distinguish among different types of radar returns (weather, birds, or aircraft); to identify diseases of the heart from electrocardiograms. (b) Noise reductionto recognize a number of patterns (voice, images, etc.) corrupted by noise. (c) Predictionto predict the value of a variable given historic values. Examples include forecasting of various types of loads, market and stock forecasting, and weather forecasting. The model built in this research paper fall into this category.

2. Gas Load Forecast System

Gas Load Forecaster System (GLFS) has been successfully implemented at major gas transmission companies and is providing load forecast accuracies of 95% and greater. Using weather, calendar, nominations, and economic data such as competing energy costs; the GLFS predicts volume/flow targets for use by Energy Solutions' transient predictive hydraulic simulation model that in conjunction with Energy Solution's system-wide compressor optimization tool will provide the plan that is needed to reach maximum revenue at minimal cost. Most of the gas industries optimize the distribution of the energy to their customers for forecasting the daily or hourly load. The operational impacts on the systems can be determined the load forecasting in the pipelined companies, so that load demands are met and the estimate of future capacity availability and find the best possible way to minimize the operational costs of meeting the demand i.e., the decisions regarding how many, at what level, and where to run compressors. Another reason for load forecasting is that all gas moving on the system is not selected. In other words, customers have certain rights to take or leave some gas in the system without having to nominate those connections and this capacity demand has to be planned. It is evident from the above reasons that a reliable load forecast is a must for any kind of operational planning. Gas load forecasting with neural networks borrows the ideas from electric load forecasting in which neural networks have been used extensively for short-term forecast - one hour up to a maximum of 24 hours [11]. Gas load forecasting however it has similarities with forecasting in other utilities (water, electric power) has different objectives. A gas load forecast system, the Tell-Future system, is built to show how neural networks work in forecasting.

Factors affecting the Load

Building a good model is most difficult part to training and testing the input data. A number of research papers [12-15] show that the following factors influence the demand of load:

Weather Conditions

Weather condition is observed that there is a strong correlation between weather (especially temperature and wind velocity) and load demand. This includes temperature, wind velocity, cloud cover, dew point, rainfall, and snowfall. In most of the situations, as the temperature goes down, the demand for gas goes up this relation is highly non-linear. Other weather effects influence the load to a lesser extent.

Calendar

Calendar includes the hour-of-day, day-of-week, and month-of-year, weekend and holiday effects. Gas load patterns show the consistent dependence on the calendar. For example, assuming all other factors remaining constant, the demand for energy at 1:00 AM when most people are sleeping is expected to be different from that at 6:00 AM when most people are getting up. Similar observations exist for the day-of-week. Though, it cannot be generalized, the middle days of the week (Tuesdays, Wednesdays, Thursdays and Fridays) behave differently from the remaining days. The month-of-year captures the seasonal effect. Holidays are again special days; they tend to produce behavior that is more like a weekend day.

Economic Information

The effect of economic factors on gas demand is non-trivial, direct influence of economic factors on gas demand can be observed in some instances such as when the customer has storage fields for introduction. This includes market gas price, price differential between gas and oil, and price differential between competitor's prices. If the market gas price is low, even if the temperature is high, there can be a high demand for gas if the customer is injecting gas into the storage field.

Similarly, if the temperature is low, if the gas price is high, customers may use the gas in the storage instead of buying new gas from pipeline companies, thus decrease the demand for load. Price differential between gas and oil plays an important role on the demand when the customer is a dual fuel use power plant. Here, depending on the price differential between gas and oil, the customer can increase or reduce gas consumption.

The above effects can be quantified and hence are possible candidates to be used as inputs for neural net training and forecasting the gas load. There are other factors, such as contractual obligations that definitely influence gas demand and these are too difficult to quantify and are therefore impossible to include as influencing variables. In addition there are a number of other factors such as maintenance or accidents on competitors' lines, that influence the demand of gas load, that at best can only be explained qualitatively.

3.The Load Forecast Model: Input Data

The input data used in this model came from a pipeline company. They stored all of their history data in different tables in database weather information in one table and hourly load history in another table. The data retrieved these data is shown as Table 1.

Date	Hour	Temperature	Wind	Load
12-08-10	00	36	3	1168
12-08-10	01	36	9	1213
12-08-10	02	36	6	1316
12-08-10	03	36	3	1417
12-08-10	04	36	3	1534
12-08-10	05	36	5	1680
12-08-10	06	36	5	1819
12-08-10	07	36	6	1967

Table 1: Input data

4. Data Processing

Given the above input data, the model can be set up to reflect up to the following six effects: (i) Temperature represented by its actual value. (ii) Wind velocity: represented by its actual value. (iii) Hour-of-day: represents the 24 hours of one day by 0, 1, 2…23 (iv) Weekday: represents Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday by 0, 1, 2, 3, 4, 5, and 6 respectively. (v) Weekend: represents Monday, Tuesday, Wednesday, Thursday and Friday as 0; Saturday and Sunday as 1. (vi) Month of year: represents the twelve months in one year by 0 to 11 respectively. Obviously, effect 1) and effect 2) are ordinal variables. They can be presented to the network by their actual values. effect 3), effect 4), effect 5) and effect 6) are categorical variables. From Section Error! Reference source not found. we know that for categorical variables, we can either use the 1-of c encoding method (which will use up to 1+1+24+7+2+12= 47 input units), or the one-effect-one-unit method (which will use only up to 1+1+1+1+1+1=6 input units). Here we adopt the second encoding method. Though this method does impose the artificial ordering on some data (effect 3, effect 4, effect 5 and effect 6), it dramatically decreases the input size, thus can simplify the system. The data set will be created automatically using the above encoding scheme from the input data file. The training set for the above input data will be encoded and shown in Table 2. All inputs to the model are linearly scaled between 0 and 1, using the minimum and maximum values corresponding to the input vector.

Temp	Wind	Hour	Week Day	Week End	Month	Load
36	3	00	6	1	1	1168
36	9	01	6	1	1	1213
36	6	02	6	1	1	1316
36	3	03	6	1	1	1417
36	3	04	6	1	1	1534
36	5	05	6	1	1	1680
36	5	06	6	1	1	1819
36	6	07	6	1	1	1967

Table 2: Training data

5. ANN Architecture

The ANN network consists of one input layer, one output layer and one hidden layer. Obviously, there is only one output unit-the load. The number of input units is also fixed, depends on how many factors are included in the model and how the factors are encoded. The number of hidden units needs to be decided by training with some test sets and shown in figure 1.

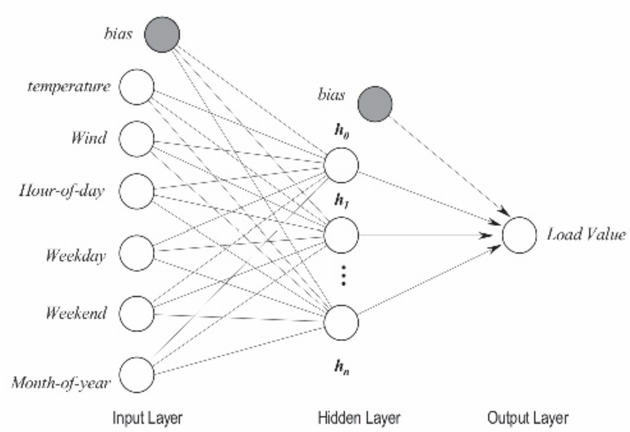

Fig. 1 ANN Architecture

The network requires enough hidden units to learn the general features of the relationship. With too many hidden units, it will cause over fitting while too few will lead to under fitting. The goal is to use as few units in the hidden layer as possible while still retaining the network's ability to learn the relationships among the data. In ANN Architecture including more than a single middle layer does not significantly improve the accuracy of the predictions. The activation functions of the hidden units are sigmoid functions while the output activation function can be either a sigmoid function or a linear function, which can be selected by the users.

Network Generalization

The Split-sample (or hold-out validation) method is used to estimate generalization error. With this method, part of the data is reserved as a test set that will not be used in the training. After training, run the network on the test set. The error on the test set provides us an unbiased estimate of the generalization error, with which we can decide whether the model is sufficiently general.

Features of the System

The Tell-Future load forecast system has several useful features: It checks the importance of each effect; It helps find optimal number of hidden units; It checks the influence of the learning rate and momentum; It displays the training and forecasting result in graphics and tabular form; It displays training errors

Training the Network

Training data which includes both input values and target values can be loaded to the system. The data are stored in the format as described previously. After setting up the effects and network parameters, we can start the training process. The process stops upon hitting the error tolerance, or reaching the time limits. The training error for each time is shown in the quick as the training process is going on and shown in figure 2.

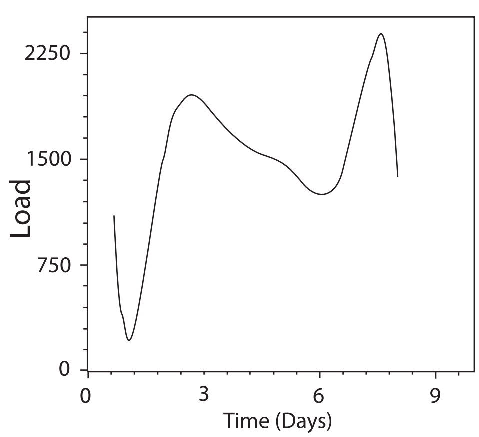

Fig.3. Training data-Load vs Time

Testing the Network

Once we finish training the network, we need to do a generalization test to see whether this model is sufficiently general. This can be done by first loading the different test sets of data available, and run the system; finally display the testing results. The results can be displayed in a format similar to Figure 2 and Figure 3. After the network has been well trained and passed the generalization test, we can load the future predicted input data to get the forecasted loads. The results can be displayed in graphic form in figure 2 or tabular form, which is similar to figure 3 except without "Actual Load" and "Error" Columns.

6. Results

The multi-layered feed-forward networks perform very well for short-term gas load forecasting. The forecast accuracy has been in excess of 90% for this model. The weather and the calendar information have great impact on the load, especially the temperature. A reasonable number of hidden units for this model is between 7 and 12, and we recommend 10. Performances are not good if the numbers are less than 5 while larger than 12 has no significant decrease in the training error and shown in figure 4. Learning rate and momentum have significant influence on the training process with the gradient descent method.

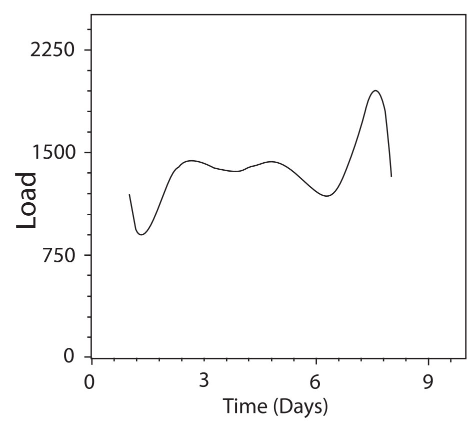

Fig.3. Actual Load vs Predicted Time

Table 2 shows the epochs that the training processes taken to meet the error tolerant (average square error is 0.0005) or reach the epoch limit (9999) with different values of learning rate and momentum, where each pair had 10 tests. It is easy to see that too large and too small learning rates converge slowly, while high momentum helps small learning rate to converge fast. The best learning rate and momentum term are 0.8 and 0.1 respectively for this model. There are no big differences between using a sigmoid activation function and a linear activation function for the output unit.

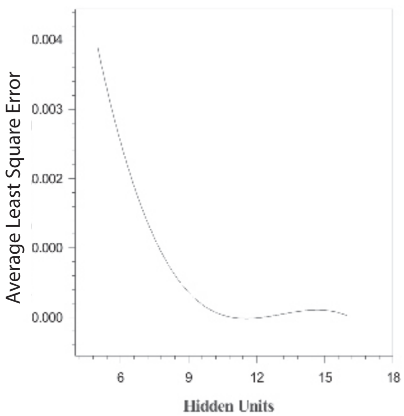

Fig. 4 Average Least Square Error Vs Hidden Units

7. Conclusions:

A multi-layer feed-forward neural network based gas load forecast model for the tell-future load forecast system is presented. The multi-layered feed-forward networks performance is well for short-term gas load forecasting. The forecast accuracy has been in excess of 90% for this model. The weather and the calendar information have great impact on the load, especially the temperature. A reasonable number of hidden units for this model are between 7 and 12, and we recommend 10. Performances are not good if the numbers are less than 5 while larger than 12 has no significant decrease in the training error. Learning rate and momentum have significant influence on the training process with the gradient drop method.

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