ANN Approach for Daily Prediction of Gas Load Forecasting

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ABSTRACT

Abstract – In these day and age the main aim of any business organization is to optimize business resources and operational processes in order to generate maximum profitability. In major gas transmission companies, the correct gas load forecasting is required in order to guarantee secure gas supply at minimal cost. Gas load prediction aids the corporation to make essential conclusions including decision on buying and selling gas cylinders, loading of gas cylinder, and infrastructure development. The main goal of this paper is to construct an experimental setup that forecast the number of cylinder requirement on next 24 hours. The important variables that researchers are going to consider in this experimental setup are related to weather conditions i.e. minimum and maximum temperature, the previous days load value and the nature of that day i.e. holiday or not. These input variables are fed into the network based on Multilayer Artificial Neural Network with back-propagation. The output of this network helps gas industry to anticipate the amount of gas cylinders needed to supply the demand. The network used in this experiment has 12 hidden layers. The real data set about 2 months from HP gas industry is used to train the ANN learning algorithm. The experiment is simulated using MATLAB 7.0.1.

KEYWORDS

Artificial Neural Network, Back propagation, Gas load forecasting

1. INTRODUCTION

In these day and age the main objective of any business organization is to optimize business resources and operational processes in order to generate maximum profitability. The corporation in this context is a major gas transmission company. The role of Gas load is very important in gas transmission and scheduling System. The correct gas load forecast is required in order to guarantee secure gas supply at minimal cost.

With the worldwide laissez-faire of the Gas industry, a gas supplier is confronted with opposing penalty costs for excessive and deficient gas supply. Load forecasting is becoming even more important, not only for system operators, but also for market operators, transmission owners, and any other market participants, so that requisite energy transactions can be scheduled, and appropriate operational plans and bidding strategies can be established. Thus, load forecasting has also become an important component of transmission and scheduling System.

A large variety of techniques from the statistical and artificial intelligence background have been evolved for making load forecaster. Similar day approach and regression method are some methods from statistical background and time series, artificial neural network and expert system are some techniques from artificial intelligence background.

Methodologies for gas load forecasting can be divided into various categories include short term forecasts, medium term forecasts and long term forecasts. In this paper we focus on daily prediction of gas load which belongs to short term forecasts.

The main goal of this paper is to constructs an experimental setup called gas load predictor that helps the gas industry to anticipate the amount of Gas cylinders needed to supply the demand. The technique used here is based on artificial neural networks. Gas load prediction aids the corporation to make essential conclusions including decision on buying and selling gas cylinders, loading of gas cylinder, and infrastructure development. It also plays an indispensable role in gas supply in gas cylinder generation, transmission, distribution and market.

2. RELATED WORK

During last decennary, many researchers have proposed distinct methods for electricity and gas load forecasting. Khotanzad, A.; Elragal, H. Dept. of Electronic Engineer, Southern Methodist Univ., Dallas, TX proposed a combination of artificial neural network (ANN) forecasters with application to the prediction of daily natural gas consumption needed by gas utilities. A two-stage system is proposed with the first stage containing three ANN forecasters. The first forecaster is a multilayer feedforward network trained with backpropagation, the second one is another multilayer feedforward network trained with Levenberg-Marquad algorithm, and the third one is a one-layer functional link network. These three separate forecasts are nonlinearly combined in the second stage using a functional link ANN combiner. A scheme is introduced to make all of the ANNs adaptive, with their weights changing throughout the forecasting phase. The performance is tested on real data from four different gas utilities for a period of several months. The results show that the proposed forecast combination approach does result in more accurate forecasts compared to using a single forecaster. The overall performance...
the system is also quite good from an operational point of view. This paper is published in IJCNN ’99 International Joint Conference on Neural Networks, 1999.

Another paper for short term natural gas consumption forecast is published in Faculty of Mechanical Engineering, Belgrade by Dejan Ivezić Assistant Professor University of Belgrade Faculty of Mining and Geology. The proposed methodology uses multilayer artificial neural networks to incorporate historical weather and consumption data. Parameters of ANN are obtained from the historical data using a Levenberg-Marquardt training algorithm. Qualities of proposed networks are tested with real data for specific urban consumption area. It was shown that ANN application presented reliable and efficient solution for proposed problem.

3. MULTI-LAYER ARTIFICIAL NEURAL NETWORK

Neuron is the simplest unit of the network. The output of the neuron as a function of input signal is given by using the following equation

\[ y = f \left( \sum_{i} (w_i x_i - \mu) \right) \]

where,
- \( y \) is the output of the neuron
- \( x_i \) are the input signals. Typically the input values are external stimuli from the environment or comes from the outputs of other artificial neurons.
- \( w_i \) are adjustable weights. The weights are real valued numbers that determine the contribution of each input. Our goal is to determine the best possible set of weight values for the problem under consideration
- \( \mu \) is called bias or threshold. It is a real number that is subtracted from weighted sum of the input value.
- \( f \) is the activation function. The activation function for the original McCulloch-Pitts neuron was the unit step function. Other activation functions include sigmoid, piecewise linear, Gaussian, identity etc.

![Fig. 1: Model of an ANN neuron](image)

Neuron is a basic element used to construct Multilayer Artificial Neural Network (MANN). MANN is an organization of a large number of neurons in several layers of network and large number of connections between these neurons in these different layers. When we consider the basic model of MANN, the first layer is the input layer, and the last layer is the output layer. Between them are one or more hidden layers. The main question here is: how many hidden layers are necessary for getting a good solution?

A single hidden layer, as depicted in **figure 2**, is always used quite safely for the majority of practical problems.

![Fig. 2: Multilayer Artificial Neural Network](image)

4. IMPORTANT FACTORS USED IN THIS FORECASTING

various factors entails when we are developing these predictor. Some of them are named as follow: time factors, weather data, possible customer’s classes, historical load customers in different categories, the appliances in the area and age, the economic and demographic data and their forecasts, the appliance sales data, and other factors. From the aforesaid factors the important factors when we are going to consider in the construction of a short term predictor include time factors, weather data, and the previous days load variable. In case of weather data we use minimum and maximum temperature of the day, for time data we use days of the weeks.

**Data set used**

The training data used to train the neural network consists of following attributes
- \( Mat \) : denotes Maximum temperature of the day
- \( Mit \) : denotes the minimum temperature of the day
- \( Wday \) : refers to particular week day
- \( Hday \) : determines if there is holiday(1) or no holiday(0).

**Previous day gas load**: determines the actual value of the gas load.

An example of the instances used in the data set is as follow
- \( Mat = 31.7, \ Mit = 17.6, \ Wday = 3, \ Hday = 0, \ Previous day gas load: = 5893 \)
The two months (58 days) data used to train this neural network and is stored in variable hdat (historical data) in our program.

5. ABOUT BACK-PROPAGATION

We are going to use Artificial Neural Network with Back Propagation, a technique with Artificial Intelligence Background, in order to make short term predictor. Artificial neural networks are used for analyzing complex problems where the relationship between the input and output variables is not well known. This method is also used where large degree of uncertainty.

In back propagation, the gradient vector of the error surface is calculated. This vector points along the line of steepest descent from the current point, so we know that if we move along it a short distance, we will decrease the error. A sequence of such moves will eventually find a minimum of some sort. The difficult part is to decide how long the steps should be.

Large steps may converge more quickly, but may also overstep the solution or go off in the wrong direction. In contrast, very small steps may go in the correct direction, but they also require a large number of iterations. In practice, the step size is proportional to the slope and to a special constant called Learning rate. The correct setting for the learning rate is application dependent and is typically chosen by experiments. This algorithm is also usually modified by inclusion of momentum term. This encourages movement in a fixed direction, so that if several steps are taken in the same direction the algorithm picks up speed.

The algorithm therefore progress iteratively through a number of epochs. On each epoch, the training cases are each submitted in turn to the network and the error calculated. This error together with the error surface gradient is used to adjust the weights and the process repeats. The initial network configuration is random and training stops when a given number of epochs elapse or when the error reaches an acceptable level or when the error stops improving.

**Epoch:**
During iterative training of a neural network an epoch is a single pass through the entire training set, followed by testing of the verification set.

**Learning Rate**
Learning rate is a control parameter of some training algorithm which controls the step size when weights are iteratively adjusted.

Following algorithm describes how learning process accomplished using Back-propagation for a single connection. Consider the following figure 3.

**Fig. 3: Single connection neural network**

1. First apply the inputs to the network and work out the output. Since the initial weights were random numbers so the initial output can be anything.
2. Next work out the error for neuron y. The error is (what we want – what we actually get), i.e. $y_{\text{Error}} = y_{\text{Output}}(1-y_{\text{Output}})(y_{\text{Target}} - y_{\text{Output}})$
3. Change the weight. Let $W_{xy}^{*}$ be the new (trained) weight and $W_{xy}$ be the initial weight. Then
   $$W_{xy}^{*} = W_{xy} + (y_{\text{Error}}x_{\text{Output}})$$
4. Calculate the Errors for the hidden layer neurons. Unlike the output layer we can’t calculate these directly because we don’t have a Target, so we Back Propagate them from the output layer hence the name of the algorithm. This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example if neuron x is connected as shown to y and z then we take the errors from y and z to generate an error for x.
   $$x_{\text{Error}} = x_{\text{Output}}(1-x_{\text{Output}})(y_{\text{Error}} W_{xy} + C_{\text{Error}} W_{xz})$$
   Again, the factor “$x_{\text{Output}}(1-x_{\text{Output}})” is present because of the sigmoid squashing function.
5. Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

**Procedure for day forecasting**
The procedure for day forecasting consists of six steps as shown in the following flowchart.

1. **Input Variable Selection:**

![Flowchart](chart.png)
Input variables such as time factors, weather data, and the previous day's load variable are initially chosen.

2. Data preprocessing:
During data collection it is inevitable to collect correct data. Improperly recorded data and observation error should be there. During data preprocessing such abnormal data are identified and corrected.

3. Training:
Each layer’s weights and biases are initialized when the neural network is set up. The network adjusts the connection strength among the internal network nodes until the proper transformation that links past inputs and outputs from the training cases is learned.

4. Simulation
Using the trained neural network, the forecasting output is simulated using the input patterns.

5. Error Analysis
input data for a day is
not hit wedy retal extal covr hday
*****************************
net-Maxima temperature
net-Minima temperature
weday-Weekday
hday-Holiday / Special day
hdct *
1.0e+003 *
0.0070
0.0070
0.0010
0.7090
Press enter to see Actual load and Forecasted load for the next day...!!!!
Actual gas load for the next day is 5893
Forecasted gas load [in number of cylinders] for this day is 5730
press a key to see error in forecasting........................
the error [in the number of cylinders is]103
test in this case is 1.7699
the accuracy of forecasting is 98.2342
press a key to see the slot .........................

During error analysis we compute the difference between the actual and forecasted day load forecasting number of cylinder. On the bases of this difference we compute error percentage and the efficiency of the day load forecaster.

6. Numerical Results
During the training phase the relationship between sum-squared error and epoch and the relationship between learning rate and epoch is shown by plotting graph as shown in figure 5.

Fig. 5: Plot defines the relationship between sum-square error and Epoch and learning rate and epoch after training phase.
The numerical computation after simulation step is shown in the figure 6.

Fig. 6: Numerical computations after simulation step
The plot gives the difference between the actual and forecasted number of cylinders is shown in figure 7.

Fig. 7: shows the relationship between actual and forecasted numbers of cylinders for next day.

7. Conclusion
An artificial neural based method that uses twelve layers feed-forward neural network and a propagation training method is presented here for day load forecasting of number of LPG cylinders. Its forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values of number of cylinders. The results suggest that this model can perform good prediction with least error and finally this neural network could be an important tool for short term load forecasting. In this method the efficiency of forecasting is greater than 98% in most of the cases. The efficiency of a particular instance given in figure 6 is 98.4742

8. Future Scope
Gas load forecasting is a key process in the running gas network in India. Over a number of years, a range of forecasting tools have been developed and research is ongoing to meet the need for even more accurate forecasts. Formerly statistical methods are used for the forecasting purpose but now machine learning models are the contender of statistical methods as they are fast, accurate and dynamic in nature. This paper will surely help those researchers that involved in the study of forecasting using machine learning techniques. We can also pull out the idea of this research paper in related fields such as electricity load forecasting, Short-term electricity demand and gas price forecasting and so on.

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