Natural Gas Load Forecasting with Combination of Adaptive Neural Networks

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Abstract

The focus of this paper is on 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 multi-layer feed-forward network trained with back-propagation, the second one is another multi-layer feed-forward network trained with Levenberg-Marquad algorithm, and the third one is a one-layer functional link network. These three separate forecasts are non-linearly 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 of the system is also quite good from an operational point of view.

I. Introduction

A gas utility, also known as a Local Distribution Company (LDC), buys its gas from a pipeline company on a daily basis. The LDC needs to provide the pipeline company with the prediction of its need for the next few days so the pipeline company can plan for the required gas demand. If the forecast error is large, the pipeline company assesses a financial penalty against the LDC. Thus, producing accurate gas consumption forecasts is quite important for a LDC.

Daily gas consumption refereed to as *Daily Gas Sendout*, is influenced by many factors. Since natural gas is mostly used for heating, the most important factor is temperature. Another important factor is wind speed, in that buildings lose more heat on a windy day than on a calm day. Heat loss is also a dynamic process, hence climatic conditions of previous days are also contributing factors to gas consumption. Many industrial customers and some commercial customers shut down over weekends; thus the day-of-week is considered a factor as well. Another relevant parameter is recent consumption trend which represents a general profile for the demand. The relationship between these parameters and the future sendout is complex and non-linear. We use the function approximation ability of the ANNs to model this relationship.

There have been relatively few attempts in the past to develop gas load forecasting systems. The linear regression based systems make up the majority of the existing computer based forecasters working in industry. In these systems, the gas demand is predicted as a linear function of the recent demand values and weather data. However, as pointed out, due to non-linear nature of the problem such methods cannot capture this relationship adequately. There has been one other attempt to build an ANN-based gas load forecaster [1]. This system uses a non-adaptive ANN.

Traditional forecasting techniques use a single forecaster to carry out the task [2]. However, this single forecaster may not be the best for all situations and/or databases. For instance, a particular ANN forecaster might work well for some databases whereas another ANN model would perform better for others. If these different forecasters are complementary, the combination of their decisions will result in improved accuracy.

The idea of forecast combination has been pursued in some recent studies [8-12] and it is shown that it can improve forecast accuracy. In this work, we use a non-linear combination strategy that utilizes an ANN combiner.

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The proposed combination strategy combines the predictions of three different ANN forecasters. Two of these forecasters are multi-layer feed-forward type and the third one is a functional link ANN [6]. The difference between the two feed-forward forecasters is in the methodology used to train them. One is trained with the classic error-back-propagation (BP) algorithm [3] whereas Levenberg-Marquardt algorithm [4,5] is used to train the other one.

A unique aspect of all the ANNs used in this work is the use of an adaptive scheme to continuously update ANN weights during the forecasting phase. In this scheme which is originally proposed in [7], the ANNs are first trained using historical data. However, the resulting trained weights are not kept constant during on-line forecasting phase. These weights are changed on a per sample basis based on the recent performance of the ANN. This adaptive scheme enables the predictors to better respond to significant load variations caused by sudden weather changes as well as tracking seasonal changes and load growth.

II. Adaptive ANN Forecasters

The proposed gas forecasting system consists of two stages. In the first stage, three adaptive ANN forecasters run in parallel and produce independent forecasts of the daily gas sendout. These forecasts are then input to the second stage, which includes a forecast combination module. The details of the three ANN forecasters are presented in the next three sections.

II. 1- AFFBP Forecaster

The first ANN forecaster is an adaptive feed-forward forecaster trained with error back-propagation (AFFBP). AFFBP is a three-layer (input, hidden, output) feed-forward perceptron ANN with sigmoidal nodes.

The BP learning algorithm is an iterative gradient descent procedure [3]. According to this algorithm, for each input in the training set learning proper weights is conducted by:

(1) Computing the error between the desired output and the network output.
(2) Feeding this error signal back level-by-level to the inputs, changing the connection weights in proportion to their responsibility for the output error.

The input vector of the AFFBP consists of the following parameters:

- Gas sendout of the past two days, $G(k-1)$, $G(k-2)$
- Average daily temperature of the past two days, $T(k-1)$, $T(k-2)$
- Average daily wind speed of the past day, $W(k-1)$
- Forecast average daily temperature of the next day, $\hat{T}(k)$
- Forecast average daily wind speed of the next day, $\hat{W}(k)$
- Day-of-week indicators

The output of AFFBP is the forecast sendout of the next day denoted by $\hat{G}_1(k)$.

As mentioned in previous section, this forecaster is made adaptive by adjusting its trained weight at the end of each day when actual weather and sendout values become available. This is accomplished by performing a small scale BP procedure which involves recent data of the past few days. This mini-training with the most recent data results in a slight adjustment of the weights and biases them toward the recent trend in data.

II. 2- AFFLM Forecaster

The second forecaster has the same structure as the first forecaster and receives the same inputs. The only difference is in the learning rule. This forecasteris trained with Levenberg-Marquardt (LM) algorithm [4,5] which is an advanced non-linear optimization algorithm. The LM algorithm is much faster than BP but its use is restricted to small size ANNs.

The output of this forecaster refered to as AFFLM (adaptive feed-forward trained with LM) is the forecast sendout of the next day denoted by $\hat{G}_2(k)$.

II. 3- AFL Forecaster

The third ANN forecaster is an adaptive functional link forecaster (AFL). AFL is a two-layer feed-forward ANN with no hidden layer and a sigmoid output node trained with a BP like learning rule [6]. The basic idea behind a functional link ANN is the use of non-linear transformation of some components of the input vector before it is fed to the input layer of the network.

The inputs selected for AFL consist of the same inputs used for AFFBP plus the following additional functional links of these variables;

- Related to previous day's sendout: $G^2(k-1)$, $\cos[\pi G(k-1)]$
- Related to previous day's temperature: $T^2(k-1)$, $\cos[\pi T(k-1)]$
- Related to next day's forecast temperature: $\hat{T}^2(k)$, $\cos[\pi \hat{T}(k)]$

The output of AFL is the forecast sendout of the next day denoted by $\hat{G}_3(k)$.

A similar adaptive strategy to AFFBP is employed here to update AFL weights during the on-line forecasting phase.

III. Combination of Forecasters

The second stage of the system consists of a combination module that mixes individual forecasts of the three described ANN forecasters. A number of linear or non-linear combination strategies can be pursued. In this work, we use an adaptive functional link ANN to perform this combination task. As such, this combiner is refered to as Adaptive Functional Link Combiner (AFLC). The AFLC receives the following 12 inputs:

$$\hat{G}_1(k), \hat{G}_1^2(k), \cos[\pi \hat{G}_1(k)]$$

$$\hat{G}_2(k), \hat{G}_2^2(k), \cos[\pi \hat{G}_2(k)]$$

$$\hat{G}_3(k), \hat{G}_3^2(k), \cos[\pi \hat{G}_3(k)]$$

$$T(k), \hat{T}^2(k), \cos[\pi \hat{T}(k)]$$

The output of AFLC denoted by $\hat{G}(k)$ is the final forecast of the system.

IV. K-day Ahead Forecasting

The proposed system performs one-day-ahead forecasting. To extend this horizon, the forecasting system is used in a recursive manner. To obtain a two-day-ahead forecast, (i.e. $\hat{G}(k+1)$), the one-day-ahead forecast, $\hat{G}(k)$, is computed first and used in place of $G(k)$ needed as an input for generating $\hat{G}(k+1)$. This procedure is repeated to generate forecasts for as many days ahead as required.

V. Experimental Study

The performance of the proposed system is tested using real data collected from four different LDCs. This study is done on an after the fact basis in which actual weather data is used in place of weather forecast so as to remove the impact of weather forecast error on the overall performance. Since the sendout prediction is more critical during the heating season (in most cases November through April), the winter period is considered in all studies. The length of training and testing periods varies according to the available data and it is usually about 400 patterns (i.e. days) for training and 200 patterns for testing. The testing is performed in a blind fashion meaning that none of the test data is used for optimizing the training process.

The performance measure is the mean absolute percentage error (MAPE) of the forecasts, computed as;

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|G(i)-\hat{G}(i)\right|}{G(i)} * 100$$

where N is the total number of the test samples (i.e., total number of days), $G(i)$ is the actual sendout of the i^{th} day, and $\hat{G}(i)$ is the corresponding sendout forecast.

Tables 1. to 3. list the MAPEs for one to three days ahead forecasting. The first three rows show the performance of the individual forecasters. The last two rows list the results if the three forecasts are simply averaged versus using the proposed combination strategy. The average of MAPEs along with the average standard deviations of them are reported in the last two columns. It can be seen that, although each of the individual ANN forecasters performs well, the proposed combination strategy does indeed improve the result significantly.

The actual daily sendout of LDC1 and their corresponding one to three days ahead forecasts for a period of five weeks are shown in Fig 1. Note that the forecasts track actual load quite closely.

Table 1. MAPEs for One-Day-Ahead Forecasts

Method	LDC 1	LDC 2	LDC 3	LDC 4	Average MAPE	Average Std. Dev.
AFFBP	2.97	5.07	3.41	5.33	4.20	4.15
AFFLM	2.96	5.06	3.44	5.17	4.16	4.38
AFL	2.92	5.19	3.42	5.50	4.15	4.23
Combination Results						
Average	2.78	4.90	3.32	5.10	4.03	4.17
AFLC	2.69	4.79	3.32	4.95	3.94	4.09

Table 2. MAPEs for Two-Day-Ahead Forecasts

Method	LDC 1	LDC 2	LDC 3	LDC 4	Average MAPE	Average Std. Dev.
AFFBP	3.28	5.40	3.61	6.11	4.60	4.30
AFFLM	3.28	5.59	3.72	5.66	4.54	4.50
AFL	3.52	5.81	3.89	5.66	4.72	4.56
Combination Results						
Average	3.09	5.38	3.59	5.69	4.44	4.31
AFLC	2.92	5.29	3.55	5.27	4.26	4.25

Table 3. MAPEs for Three-Day-Ahead Forecasts

Method	LDC 1	LDC 2	LDC 3	LDC 4	Average MAPE	Average Std. Dev.
AFFBP	3.67	5.34	3.71	6.61	4.83	4.52
AFFLM	3.52	5.47	3.73	6.10	4.71	4.56
AFL	4.24	6.19	4.26	5.97	5.17	4.81
Combination Results						
Average	3.39	5.36	3.73	6.08	4.64	4.40
AFLC	3.15	5.37	3.59	5.54	4.41	4.30

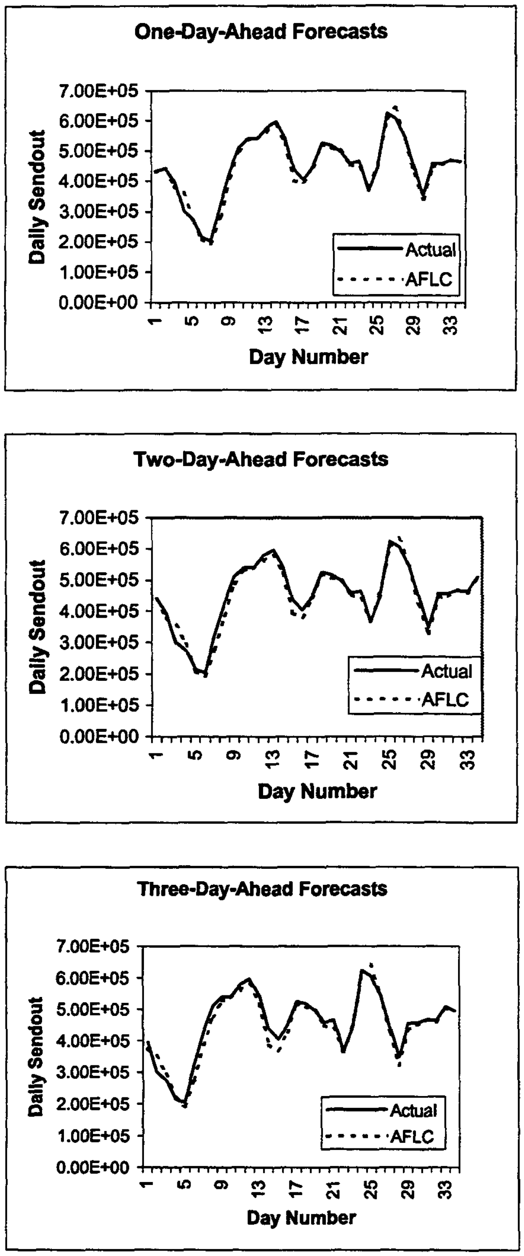

Figure 1: LDC1 actual daily sendouts and their corresponding forecasts for a five week period

VI. Conclusions

This paper proposes a novel two-stage system for gas demand forecasting. The first stage consists of three adaptive ANN forecasters that differ in their topology and/or training algorithm and/or type of inputs received. The second stage performs a non-linear combination of the forecasts via a functional link ANN

The performance is tested on real data from four gas utilities for a period of several months. It is shown that the proposed forecast combination approach does result in more accurate forecasts compared to using single forecasters.

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