A Study of Short-Term Load Forecasting in Buildings Using Artificial Neural Networks.

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Abstract

Load forecasting the essential part of an efficient power system planning and operation. In modern society, the building energy consumption accounts for a significant number of total energy consumption. Therefore, an efficient use of energy in buildings becomes more important, furthermore the load forecasting for the building domain is essential work. This paper presents an artificial neural network (ANN)-based model for building short-term load forecasting (STLF), which uses weather data as well as past load data. The performance of the prediction model is evaluated using in terms of the mean absolute percentage error (MAPE) and the simulation results show that the proposed method can significantly improve forecasting performance.

Keywords: artificial neural networks (ANNs), building energy consumption, load forecasting

1 INTRODUCTION

Improving accuracy of load forecasting is important for the efficient and secure operation of a power grid. Nowadays, the power grid is not limited to national grid. One of the most important examples is microgrid, which consists of multiple distributed energy resources (DERs), energy storage units, and loads. Microgrid can operate either with help of main grid, i.e. grid-connected mode or without it, i.e., stand-alone mode [1,2].

The size of power grid can be further reduced to a residential grid or building grid. In modern society, the building energy consumption accounts for a significant number of total energy consumption. Therefore, accurate short-term load forecasting (STLF) in building domain is important.

In this paper, we focus on the building energy usage and present an artificial neural network (ANN)-based load forecasting method for STLF in buildings. We first analyze the load pattern of a building in Soongsil University. Then, several STLF methods are investigated such as regression-based and ANN-based methods. The proposed STLF predicts the hourly loads over the next 24h in a day by using weather and past load data. From the experimental case studies, ANN-based method outperforms the regression-based method, and an ANN which uses weather data as well as past load data performs the best.

The rest of paper is organized as follows. In Section 2, we briefly explain ANN base load forecasting method and propose ANN-based STLF methods. We present a case study using load data from a campus building in Section 3. Finally, we conclude our work in Section 4.

2 BUILDING LOAD FORECASTING

This section briefly presents the ANN-based load forecasting method and an ANN-based STLF method is proposed.

2.1 Artificial Neural Network-based Load Forecasting

Electric load forecast using ANN has been developed and extensively applied since the early 1990's. ANN is a mathematical tool and it is originally inspired by the way the human brain processes information. It is suitable for dealing with the nonlinear problem and the most widely used forecasters for predicting nonlinear signals due to their flexibility and easy implementation [3], [4]. Compared to regression-based model, ANN-based model has more number of weights, resulting in flexibility to model non-linear problems. ANN has several advantages such as clear model, easy implementation, good flexibility and robustness.

In electric load forecasting area, ANN is one of the most popular options due to their ability to automatically learn from experience and adapt themselves. There are many ANNs-based load forecasting methods and the structure of ANN is highly dependent on the ANN model. Rumelhart et al. have proposed an ANN method using multi-layer perceptron (MLP) [5]. A radial basis functions network-based load forecast method has been proposed in [6]. Elman et al. have proposed recurrent neural networks-based method [7,8]. Cascade combinations have also been employed for a wide array of tasks related to data analysis, prediction, and estimation [9,10].

Fig. 1 shows an example of MLP ANN architecture. The MLP ANN consists of three layers: input, hidden and output layers. Neurons in each layer are connected to the neurons of the next layer by synaptic weights. These synaptic weights are determined by training an ANN so that a performance function E is minimized for the training set. The performance function is given by

$$E = \frac{1}{N}\sum_{i=1}^{N}(target_i - output_i)^2,$$

where $target_i$ and $output_i$ are the actual and forecasted outputs of the ANN for i-th sample data, respectively, and N presents the number of samples employed for training.

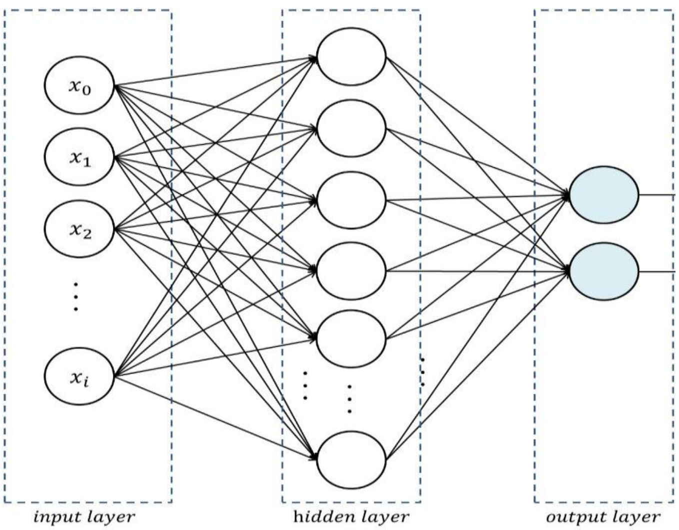

Fig.1. An example of MLP ANN architecture

2.2 The Proposed ANN-based STLF method.

The proposed STLF predicts the hourly loads over the next 24h in a day by using weather and past load data.

1) ANN type and training algorithm: In this study, we use MLP ANN, which is shown in Fig. 1, and use the Levenberg-Marquardt optimization algorithm for training algorithm. Levenberg-Marquardt algorithm is one of the most popular algorithms for training multilayer feed forward ANNs and it uses a back propagation method. Levenberg-Marquardt algorithm transits between the steepest descent method and the Newton method.

2) Range of forecasting: The building load data used in this paper is the actual electricity consumption load from a campus building in the Soongsil University, Seoul, Korea. Fig. 2 shows sample load data for the building for a week in November 2015. Since daily load curves in weekdays are very different from that in weekends, we focus on the daily load curve in this paper. The load forecasting for the weekends left as a future work. We use Tuesday, Wednesday, Thursday and Friday as weekday's load curve because Monday generally has a different characteristic from the other weekdays.

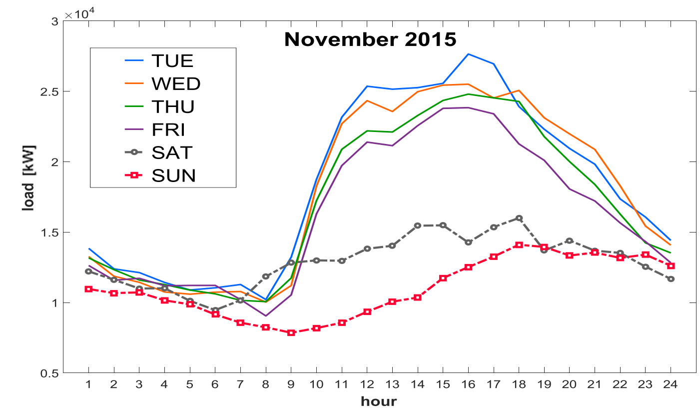

Figure 2. A week load data in November 2015.

3) Characteristics of the daily load curve: To predict the electric demand precisely, it is important to understand a daily load curve's characteristics [11]. Fig. 3 shows a typical load curve for the campus building. It can be divided into three periods. The first period (from 0:00 to 7:00) has little electricity consumption and it gradually decreases. The load in second period (8:00 to 15:00) dramatically increases while that in third period (16:00 to 23:00) sharply decreases. Table 1 summarizes these characteristics. Therefore, to get a more accurate load forecasting, each day is divided into the three periods.

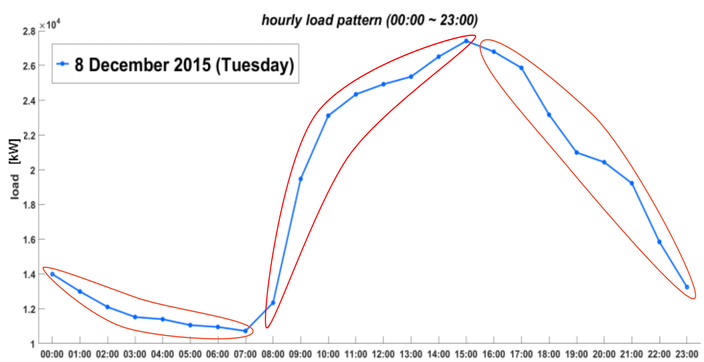

Figure 3. Daily load curve on December 8, 2015.

Table 1. Forecasting hourly load for each period

ANN 1	00:00~07:00	the load curve decreases slowly.
ANN 2	08:00~15:00	the load curve increases significantly.
ANN 3	16:00~23:00	the load curve decreases significantly.

4) Input parameters for the proposed ANN-based STLF:

To predict the next 24h hourly load, a proper selection of input parameters is very important. To this end, we first analyze correlations between past load data and the predicted day. Table 2 shows the correlation coefficient between them. The forecasted load data have higher correlation coefficient with L_{d-1}, L_{d-2}, L_{d-7}, so we use all the three data as input parameters. Note that, in this paper, "*d-1*" means a day in week, which is one day before the day. Since weather data significantly affect the load, it is used as input parameter. Among various weather data, we use the daily maximum and minimum temperatures.

According to the algorithm and input parameters, four load forecasting methods are presented in this paper. All the four methods have the same output parameter. That is, the next 24h hourly load. Case 1 use regression algorithm and past load data of the three days, i.e., L_{d-1}, L_{d-2}, and L_{d-7}. On the other hand, cases 2, 3, and 4 use ANN algorithm. Cases 2 and 3 only use past load data while case 4 uses weather data as well as past load data. Case 2 has one ANN, and it is used to predict the whole 24h load data. In case 3, there are three ANNs and each ANN takes charge of one period as shown in a row in Table 1. Case 4 also have three ANNs and uses 9 input parameters which consist of past load data and weather data. Table 3 summarizes the input and output parameters for the four cases.

Table 2. Correlation coefficient for load L

	$L_{(d-1)}$	$L_{(d-2)}$	$L_{(d-7)}$
$L_{(d)}$	0.9830	0.9829	0.9858

Table 3. Variables in the input and output layer

	Input	Output
Case 1 **(Regression)**	$L_{(d-1,h)}$ $L_{(d-2,h)}$ $L_{(d-7,h)}$	$L_{(d,h)}$ $h=1,\cdots,24$
Case 2 **(ANN)**	$L_{(d-1,h)}$ $L_{(d-2,h)}$ $L_{(d-7,h)}$	
Case 3 **(3 ANNs)**	$L_{(d-1,h)}$ $L_{(d-2,h)}$ $L_{(d-7,h)}$	
Case 4 **(3 ANNs)**	$L_{(d-1,h)}$ $T_{(d-1)_{min}}$ $T_{(d-1)_{max}}$ $L_{(d-2,h)}$ $T_{(d-2)_{min}}$ $T_{(d-2)_{max}}$ $L_{(d-7,h)}$ $T_{(d)\ min}$ $T_{(d)\ max}$	

3 EXPERIMENTAL RESULT FOR CASE STUDIES

3.1 Evaluation Settings

Data used for this work is the electric consumption of building in Soongsil University for three months (October 2015 - December 2015). The STLF is performed for weekdays in each month. Among the whole data set, 70%, 15%, and 15% of data are used for learning, validation, and test of the ANN model, respectively. The optimal number of hidden neurons is found through simulations.

We use mean absolute percentage error (MAPE) to evaluate the performance of the forecasting model. It is given by:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{L_{f,i}-L_{a,i}}{L_{a,i}}\right| \times 100 \quad [\%],$$

where $L_{f,i}$ and $L_{a,i}$ denote the forecasted and actual load for i-th sample.

3.2 Result

The forecasting results obtained using the four methods in Section 2 are presented in Tables 4-6.

Table 4. MAPE values of the load forecast method (Oct. 2015)

MAPE [%]	Case 1	Case 2	Case 3	Case 4
00:00 - 07:00	4.7182%	3.2211%	2.6408%	1.2393%
08:00 - 15:00	3.3440%		2.2656%	1.1301%
16:00 - 23:00	3.5705%		2.5256%	0.8899%
Total	***3.8776%***	***3.2211%***	***2.4773%***	***1.0865%***

Table 5. MAPE values of the load forecast method (Nov. 2015)

MAPE [%]	Case 1	Case 2	Case 3	Case 4
00:00 - 07:00	4.4513%	3.9943%	3.3991%	1.3018%
08:00 - 15:00	5.0661%		3.0672%	1.1689%
16:00 - 23:00	5.4029%		3.2944%	0.9183%
Total	***4.9735%***	***3.9943%***	***3.2536%***	***1.1297%***

Table 6. MAPE values of the load forecast method (Dec. 2015)

MAPE [%]	Case 1	Case 2	Case 3	Case 4
00:00 - 07:00	9.0165%		3.1630%	1.3236%
08:00 - 15:00	6.9183%	4.1988%	3.5354%	1.0919%
16:00 - 23:00	7.6272%		3.1631%	0.9168%
Total	***7.8540%***	***4.1988%***	***3.2872%***	***1.1676%***

Generally, ANN-based methods outperforms regression-based method. The performance improvement of case 2 than case 1 is about 28% on average. The method of dividing a day into three groups also improves the performance by 21%, i.e., case 3 in comparison with case 2. MAPE of case 4 further improves by 62% compared to case 3.

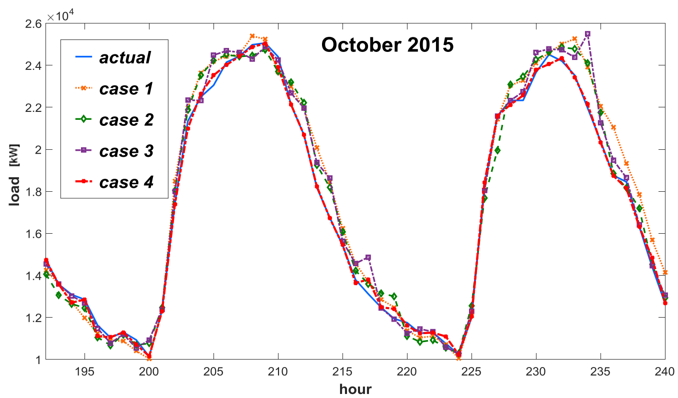

Figure 4. Actual load against forecasted load (Oct. 2015)

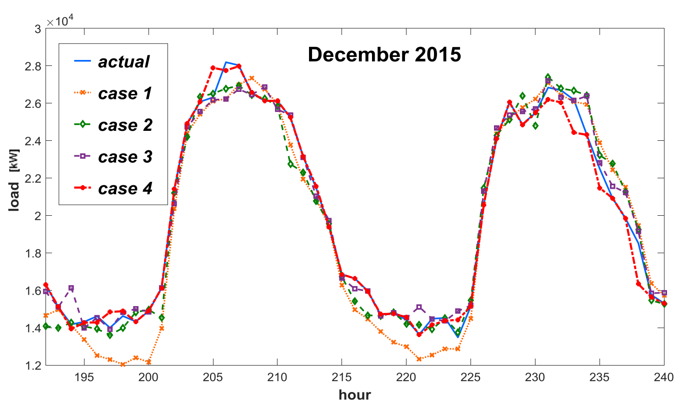

Figure 5. Actual load against forecasted load (Dec. 2015)

To understand the forecasting performance improvement more detail, Figs. 4 and 5 show examples of actual forecasted loads. As shown in Fig. 4, when the daily load curve of forecasted day is similar to that of the previous day, all the four methods accurately forecast the actual load. However, when the present day and the previous day shows different load curve, the methods without weather data performs poorly. Therefore, it is confirmed that the weather data is essential for accurate load forecasting in buildings.

4. Conclusion

In this paper, we analyzed the daily load curve in a campus building and proposed artificial neural network (ANN)-based short term load forecasting (STLF) method. ANN-based methods are suitable to model the STLF in buildings because of complex and nonlinear feature of the problem. The performances of four forecasting methods are evaluated by an actual building load data in Soongsil University. The results show that ANN-based methods outperform the regression-based method. To improve the performance of ANN-based forecasting method, a day is divided into three periods according to their characteristics, and different ANNs are used for them. Since the electric load in building heavily depends on weather, the ANN that uses weather data and three ANNs for the three periods shows the best performance, i.e., MAPE 1.13%. The reason for the good accuracy is that the weekday load of the campus building shows repetitive load pattern in the same semester. In future work, we need to develop forecasting method for weekends. Also, we need to further analyze important factors which affect the load curve.

ACKNOWLEDGEMENT

This work was supported in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20134010200570) and in part by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (2015R1C1A1A02037774).

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