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Short-term energy consumption prediction in Korean residential buildings using optimized multi-layer perceptron

Fazli Wahid*, Do Hyeun Kim

Dept. of Computer Engineering, Jeju National University, Jeju City, South Korea

Corresponding author: wahid_uomian@hotmail.com

Abstract

For the designing and management of energy production and storage systems, the prediction of household short-term energy consumption is of vital importance. In this paper, we present a prediction methodology for short-term energy consumption using optimized multi-layer perceptron. A total of 20 models of multi-layer perceptrons (MLP) with different architectures were developed for hourly energy consumption prediction. For the determination of best combinations of learning algorithms, hidden layers' transfer functions and output layer functions, different types of training algorithms and hidden layer and output layer functions were considered. Two main training algorithms, namely scaled conjugate gradient, and Levenberg-Marquardt back propagation algorithms, were used for training. In the hidden layer, tangent and logarithmic sigmoid equations were used as activation functions and linear, logarithmic sigmoid and tangent sigmoid were used as output functions. The evaluation of performance of models was based on mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE).The performance and feasibility of the proposed model have been tested on real data of some residential buildings of Seoul, Republic of Korea for a specific period of time. We had total of 14260 (20 Apartments x 31 Days x 23 Hours) samples' data which were divided into 70% (9982 samples) training and 30% (4278 samples) testing.

Keywords: Hourly prediction; multi-layer perceptron; residential buildings; short-term energy consumption

1. Introduction

The prediction of energy consumption is very important for the planning and operation of energy management systems. The prediction is important for finding future energy demand values. This plays an important role in production, delivery and reselling of energy. The reliability of power systems can be improved by correct prediction of future energy usage. An efficient energy consumption prediction can lead to better economy, fuel management and hydrothermal commitment. Energy consumption prediction can be mainly divided into three main categories namely short-term prediction, medium-term prediction and long-term prediction Mitchell *et al*. (1986).

In the literature, many techniques have been applied for the energy consumption prediction with varying degrees of accuracy. Hippert *et al*. (2001) and Carpinteiro *et al*. (2004) have used artificial neural network (ANN) for short-term energy prediction. For load forecasting, Gross & Galiana (1987) used regression models and times series. For different types of forecasting, general methodologies have been discussed by the authors in (WASU). Kalman filter has been used by Irisarri *et al*. (1982) for short-term load forecasting. In Ali & Kim (2013), authors used Kalman filter for prediction whereas GA was used by Ali & Kim (2015) for prediction and management of energy in residential buildings. Fuzzy logic has been used by Kiartzis *et al*. (2000) and Miranda & Monteiro (2000) whereas fuzzy neural networks have been used by Bakirtzis *et al*., 1995 and Srinivasan *et al*., (1995) for short-term load forecasting.

Many authors have used hybrid models in which they have combined artificial neural network with statistical methods. Examples of these models are hybrid models with Bayesian inference (Saini, 2008; Lauret *et al*., 2008), wavelet transform (Yao *et al*., 2000; Nengling *et al*., 2006), self-organization map (SOM) Amin-Naseri & Soroush (2008) and particle swarm optimization (PSO) El-Telbany & El-Karmi (2008). The objective of this paper is to predict the next hour energy consumption using multi-layer perceptron with different architectures. Similar to previous works in energy consumption prediction, historical data of consumption has been used to predict future consumption. In Wahid & Kim (2015), authors applied random forest for energy consumption prediction in residential buildings whereas K nearest neighbour was applied for the same purpose by Wahid & Kim (2016). In Wahid & Kim (2016), artificial bee colony was applied by the authors for energy management in residential buildings.

Multi-layer perceptron is an artificial neural network with one or more hidden layers. Different architectures of Artificial Neural Network have been used for different types of modelling for many years in different disciplines including medicine, mathematics, economics, engineering, meteorology, psychology, hydrology, neurology and other areas (Chow *et al*., 2002; Kumar *et al*., 2002; Sözen & Akçayol, 2004; Feyza *et al*., 2016). They have gained much popularity since their first inception in 1943 (McCulloch & Pitts, 1943) due to their strong capability for solving prediction problems with variables having stochastic nature, unknown or non-linear variations, or less controlled environment required for their determination (Moustris *et al*., 2011). Due to their flexibility and less assumption-dependency, the physical processing between their inputs and outputs is not needed (Morid *et al*., 2007).

Artificial neural networks learn from the variations in the historical data and make prediction based on these variations. In order to perform prediction, neural networks create an input-output mapping system. For training and testing of any model of neural network, the inputs and their corresponding outputs are necessary (Şahin, 2013).

2. Material and method

2.1 Data set

In this paper, the hourly energy consumption prediction has been carried out using multi-layer perceptron. In this study, real data of twenty apartments of Seoul, Republic of Korea for the month of January 2010 has been used. For the prediction of next hour consumption, we have a total of 14260 (20 Apartments x 31 Days x 23 Hours) hours.

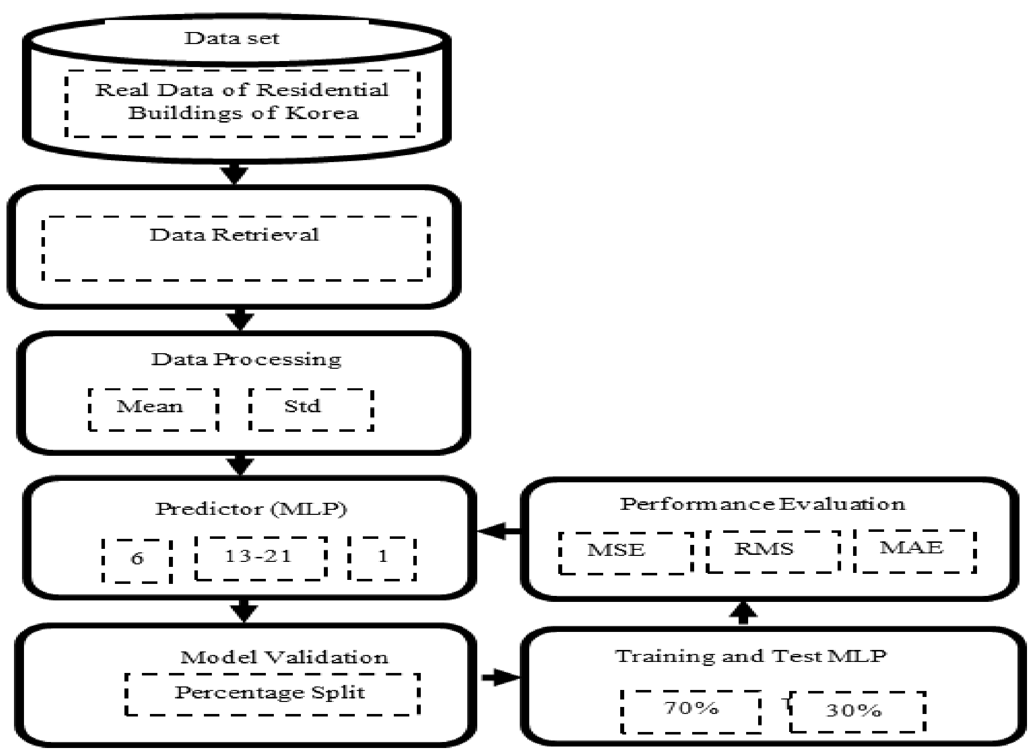

Fig. 1. Proposed method

Figure 1 shows the proposed method for short term energy consumption prediction. The proposed method consists of different stages e.g. data retrieval, data processing, prediction, model validation, training and testing of multi-layer perceptron and performance evaluation. Each of these stages is explained in the coming sections.

2.2 Data retrieval

In this stage, the data set containing data for processing is retrieved from the excel database. For the prediction of next hour energy consumption, we have historical data that contains the previously consumed energy on hourly basis.

2.3 Data processing

In this stage, the hourly consumed data is selected from the retrieved data; the mean and standard deviation of the daily consumed data based on hourly consumption are computed. The mean and standard deviations are computed using following formulas.

2.3.1 Mean

Mean represents the average of all the hourly consumed power over the whole day represented by Equation 1.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

Where μ represents the mean of all the hourly consumed power over the whole day. x_i represents the power consumption over ith hour of the day where i = 0,1,2,…,23. N represents the total number of hours i.e. 24.

2.3.2 Standard deviation

Variance represents the variations in the hourly consumed power over the whole day and standard deviation is the square root of the variance which is represented by Equation 2.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (2)$$

Where σ represents the standard deviation and all other terms in the equation have been explained in the Equation (1).

2.4 Prediction using multilayer perceptron

A multi-layer perceptron is a complex structure made up of layers of non-linear elements called neurons. A multi-layer perceptron with three layers is shown in Figure 3. The mathematical computation involved inside a single perceptron is shown as follows. Suppose, we have input signal $x_1, x_2, x_3, \ldots, x_n$; synaptic weights for each neuron k are $w_{k1}, w_{k2}, w_{k3}, \ldots, w_{kn}$; then u_k is the linear combiner output due to inputs and is given by Equation 3.

$$uk = \sum_{i=1}^{n} w_k x_i \quad (3)$$

If b_k is applied as bias and Φ as an activation function, then the output y_k of neuron can be computed by using Equation 4

$$y_k = \Phi(u_k + b_k) \quad (4)$$

The values supplied to b_k increase or decrease the values of inputs depending on whether it is positive or negative. A simple neuron model with externally provided values of bias is shown in the following Figure 2 (a). The effect of bias b_k is the like to apply affine transformation to the output u_k of the linear combiner in the model as shown in the Figure 2 (b) and given by the Equation 5.

$$v_k = u_k + bk \quad (5)$$

Depending on the positive or negative values of bias b_k, the relationship between the induced local field or activation potential v_k of a neuron k and u_k can be modified as shown in the Figure 2 (b)

The combination of Equations (3), (4) and (5) can be formulated as

$$vk = \sum_{i=0}^{n} w_{ki} \quad (6)$$

$$y_k = \Phi(v_k) \quad (7)$$

Mainly three different types of transfer functions namely linear function represented by χ(x), tangent sigmoid function represented by ϕ(x) and logarithmic sigmoid function represented by ψ(x) are used in the hidden layers and output layer of multi-layer perceptron and these are described as follows Vogl et al. (1988).

$$\chi(x) = \text{linear}(x) \quad (8)$$

$$\phi(x) = \frac{2}{1+e^{-2x}} - 1 \quad (9)$$

$$\psi(x) = \frac{1}{1+e^{-x}} \quad (10)$$

In order to make the best predictive model, Equations (8), (9) and (10) may be used in different combinations in hidden and output layers (Şahin, 2012; Karlik & Olgac, 2011; Harrington, 1993).

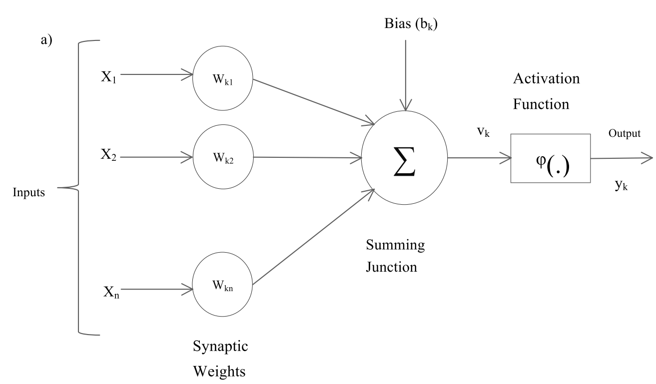

Fig 2. a. A simple neuron model with externally provided values of bias (Deo & Şahin, 2015).

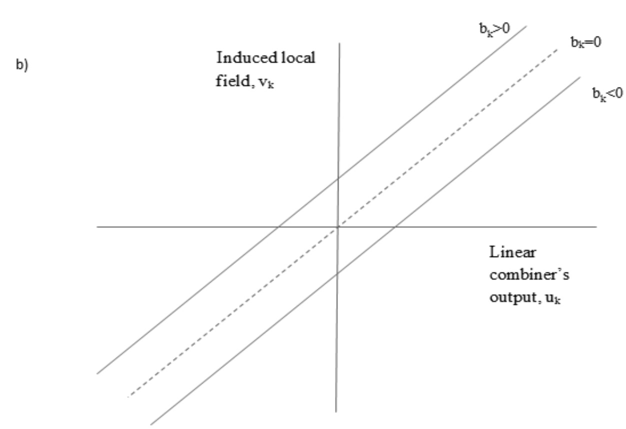

Fig 2. b. The effect of bias b_k to apply affine transformation to the output u_k of the linear combiner in the model (Deo & Şahin, 2015).

2.4 Model validation/training and testing

In order to validate each of the 20 models developed, we have adopted a percentage split mechanism in which the whole data is divided into some specific ratio for training and testing. For experimentation, the data has been divided into 70% training and 30% testing samples. Keeping in consideration, this division a total of 9982 (14 Apartments x 31 Days x 23 Hours) samples have been used for training whereas 4278 (6 Apartments x 31 Days x 23 Hours) samples have been used for testing.

2.5 Performance evaluation

As shown in the Table 1, the performance of the models has been measured using mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE). In order to calculate these measurements, the following formulas have been used

$$MS = \frac{1}{n}\sum_{i=1}^{n}(A-P)^2 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A-P)^2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|AP| \tag{13}$$

Where n is the total number of observations, A is the actual value and P is the predicted value. In the coming sections, different graphs showing the actual values, predicted values and absolute errors observed during prediction are shown.

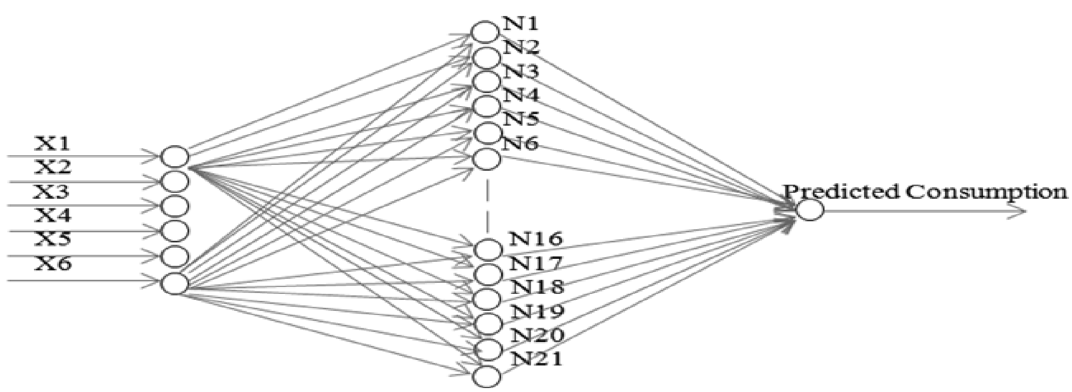

Fig. 3. Multi-layer perceptron architecture for hourly energy consumption prediction.

3. Experimental results and discussion

All simulations have been performed on Intel (R) Core (TM)2 Quad CPU A9550 @ 2.83GHz with MATLAB installed on it. In this research, instead of testing the sensitivity of input parameters, different types of network training functions, hidden layer transfer functions and output layer transfer functions were used to find out the best model for prediction. All the network models have six perceptrons in the input layer, one perceptron in the output layer and the number of perceptrons in the hidden layer was varied from 13 to 21 for finding the best combination with different types of training function, hidden layer transfer functions and output layer transfer functions. As there exists no defined mathematical formula for the determination of number of neurons in the hidden layer, trial and error mechanism has been used for deciding the number of neurons in the hidden layer (Şahin, 2012).

The input parameters and their importance is described as follow

- The apartment number takes values from 1 to 20 and this is important because different apartments have different hourly energy consumption variations over the whole month
- The day takes values from 1 to 31 and it is important because on different days, an apartment has similarities in hourly consumption
- Hour takes values from 1 to 24 and it is important because each apartment utilizes different amount of energy in each hour with some similarities in consumption
- Past consumption takes real values of energy consumed during last hour and it has overall effect on next hour consumption in the whole data set
- The mean of 24 hours hourly consumption has an overall effect on each hour consumption of the day
- The standard deviation of 24 hours hourly consumption has overall effect on each hour consumption of the day

Figure 3 shows architecture of MLP used for prediction. X1, X2, X3, X4, X5 and X6 represent apartment number, day, hour, hourly consumed energy, mean of 24 hours hourly consumption and standard deviation of the 24 hours hourly consumption, respectively. Table1 shows parameters of all models for prediction of hourly consumption of energy. N1, N2, N3,…,N21 show the number of neurons in the hidden layer of the multi-layer perceptron.

Table 1. Network models with different training algorithms, hidden layer and output layer transfer functions and different performance parameters.

Model	Network training algorithm	Hidden Layer Transfer Function	Outer Layer Transfer Function	Network Structure	Network Training Time(S)	MSE	RMSE	MAE
M1	Trainscg	Tansig	Tansig	6-13-1	94	0.0876	0.2959	0.2006
M2	Trainscg	Tansig	Tansig	6-15-1	109	0.0848	0.2912	0.2001
M3	Trainscg	Tansig	Tansig	6-17-1	109	0.0852	0.2918	0.2008
M4	Trainscg	Tansig	Linear	6-21-1	104	0.0860	0.2932	0.2006
M5	Trainscg	Tansig	Linear	6-19-1	103	0.0837	0.2893	0.1988
M6	Trainscg	Tansig	Linear	6-17-1	117	0.0844	0.2905	0.1990
M7	Trainscg	Tansig	Logsig	6-17-1	113	0.810	0.90	0.8673
M8	Trainscg	Tansig	Logsig	6-21-1	107	0.8782	0.9371	0.8670
M9	Trainscg	Tansig	Logsig	6-15-1	74	0.8082	0.8989	0.8670
M10	Traincgp	Tansig	Linear	6-15-1	136	0.0841	0.29	0.1995
M11	Traincgp	Tansig	Linear	6-17-1	139	0.0853	0.2920	0.2004
M12	Traincgp	Tansig	Linear	6-19-1	132	0.0855	0.2924	0.1995
M13	Trainlm	Tansig	Linear	6-19-1	88	0.0869	0.2947	0.1995
M14	Trainlm	Tansig	Linear	6-17-1	92	0.0853	0.2920	0.1991
M15	Trailm	Tansig	Linear	6-15-1	80	0.0862	0.2935	0.2002
M16	Trainlm	Tansig	Tansig	6-17-1	93	0.0868	0.2946	0.1710
M17	Trainlm	Tansig	Tansig	6-19-1	98	0.0860	0.2932	0.2003
M18	Trainlm	Tansig	Tansig	6-21-1	102	0.0858	0.2929	0.2004
M19	Trainlm	Logsig	Tansig	6-17-1	93	0.0855	0.2924	0.1994
M20	Trainlm	Logsig	Tansig	6-19-1	94	0.0856	0.2925	0.1997

The model 5 (M5) has been bolded because this model gives the best performance result. It is evident from the table that the best result is given by the network in which the network training algorithm is trainscg, hidden layer function is tansig and output layer function is linear. The graphical representation of prediction results for the best model (M5) is presented in the following section. Figure 4-11 show actual consumed power, predicted consumed power and the errors observed in prediction during different days of the month for the best observed model (M5). It is evident from the figures that the actual consumption and the predicted consumption follow almost the same pattern which shows the effectiveness of the proposed model. In each of the following graphs, Y-Axis shows the energy consumption in kilo watt hours and the X-Axis shows the hour in which the energy has been consumed. Figure 5, Figure 7, Figure. 9 and Figure 11 show the absolute error observed in the prediction of multi-layer perceptron as well.

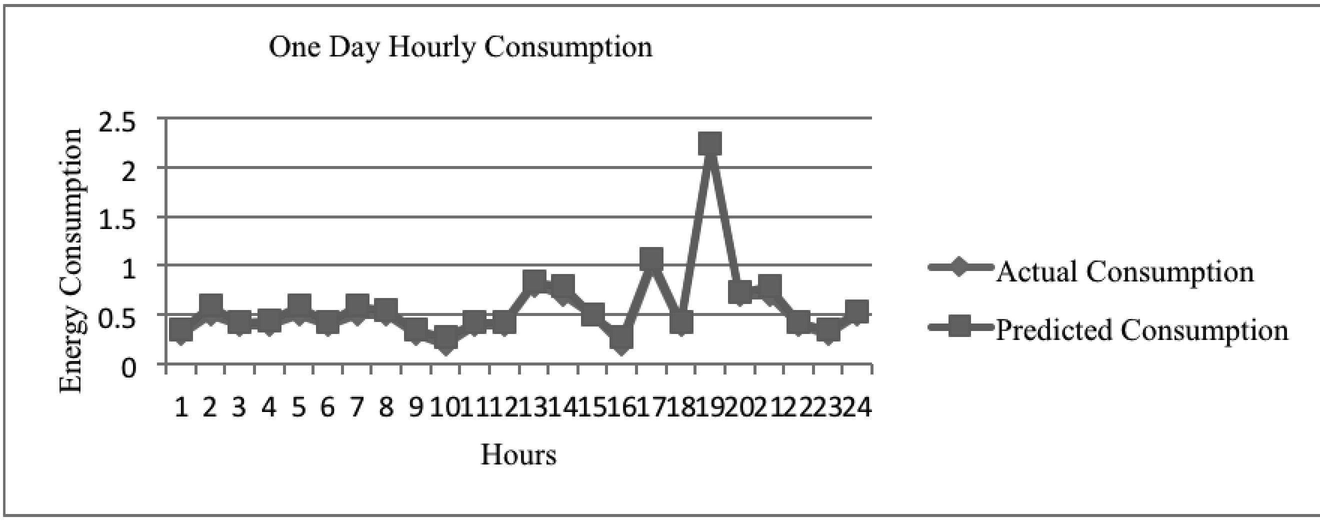

Fig. 4. The actual and predicted values of energy consumption of a single apartment during one day of the month

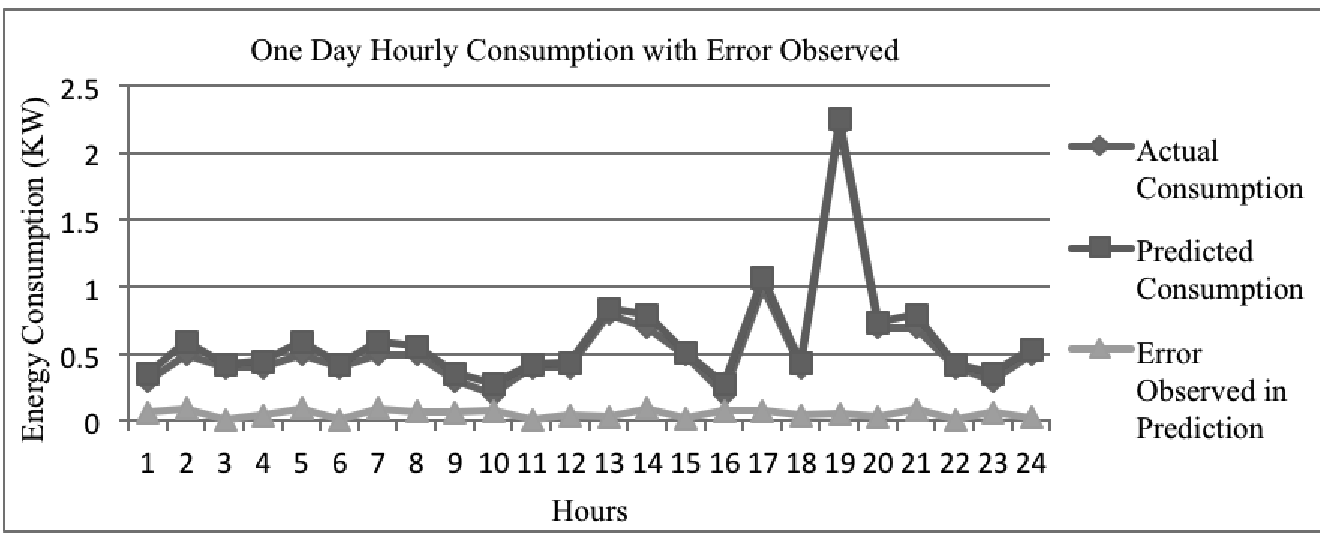

Fig. 5. The actual and predicted values of energy consumption of a single apartment during one day of the month with the observed error in prediction

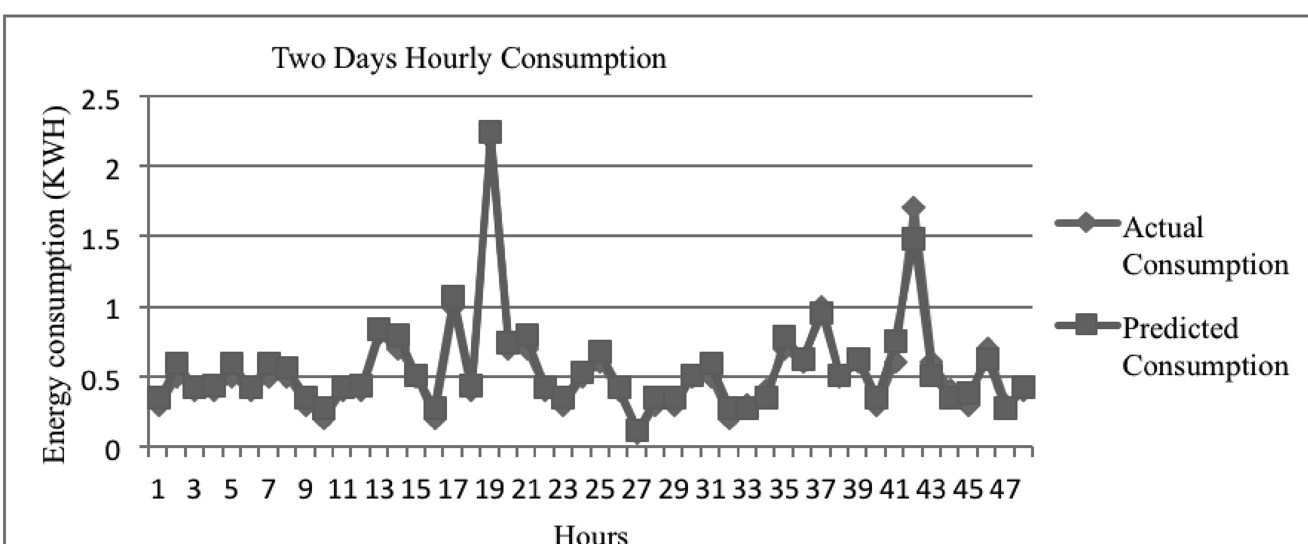

Fig. 6. The actual and predicted values of energy consumption of a single apartment during two days of the month

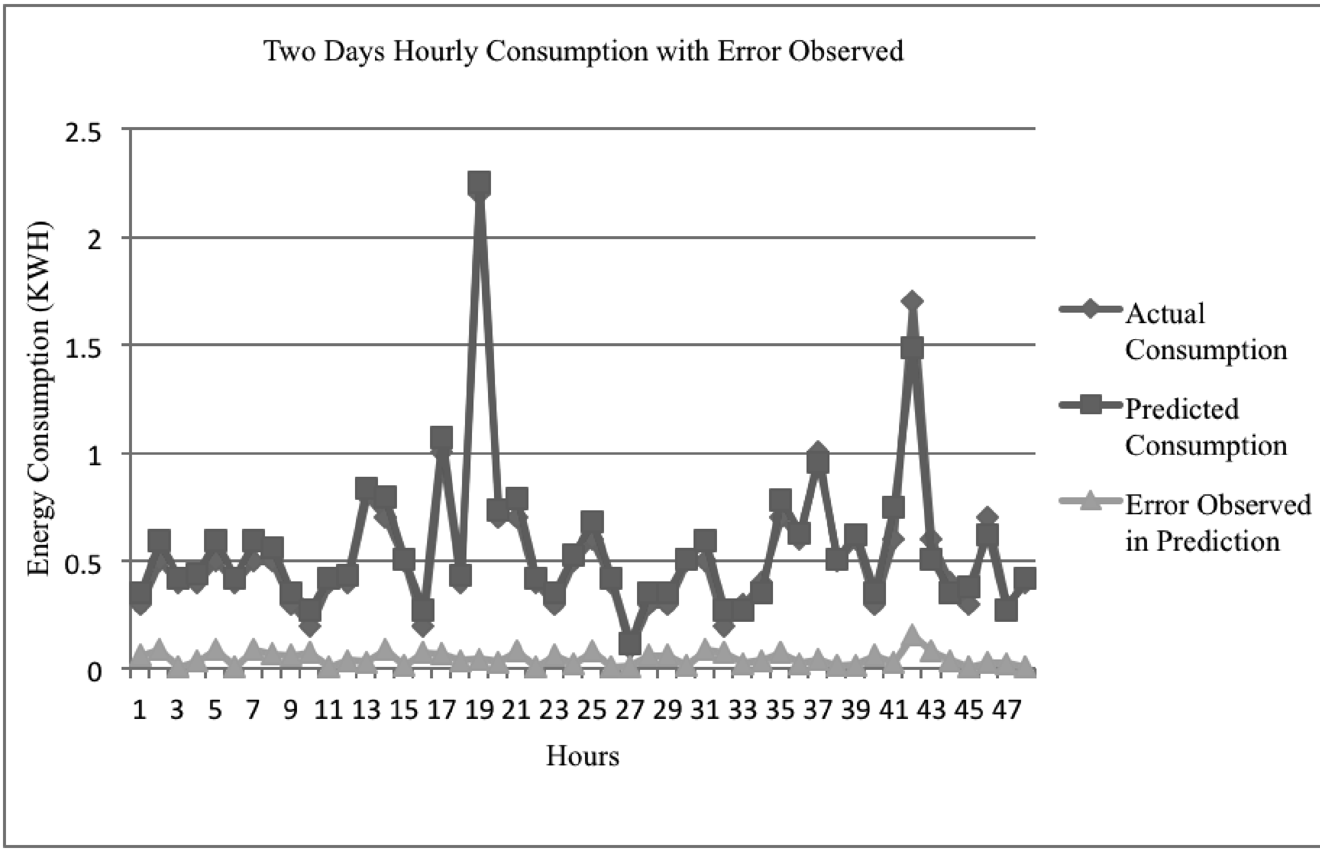

Fig. 7. The actual and predicted values of energy consumption of a single apartment during two days of the month with the error observed in prediction

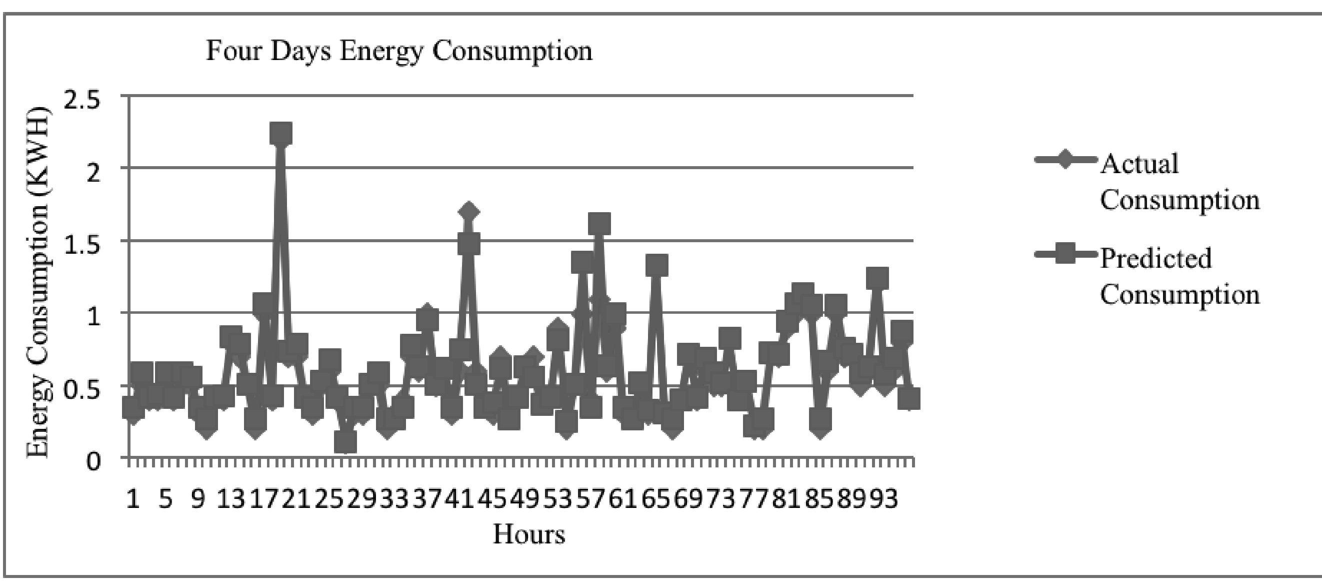

Fig. 8. The actual and predicted values of energy consumption of a single apartment during four days of the month

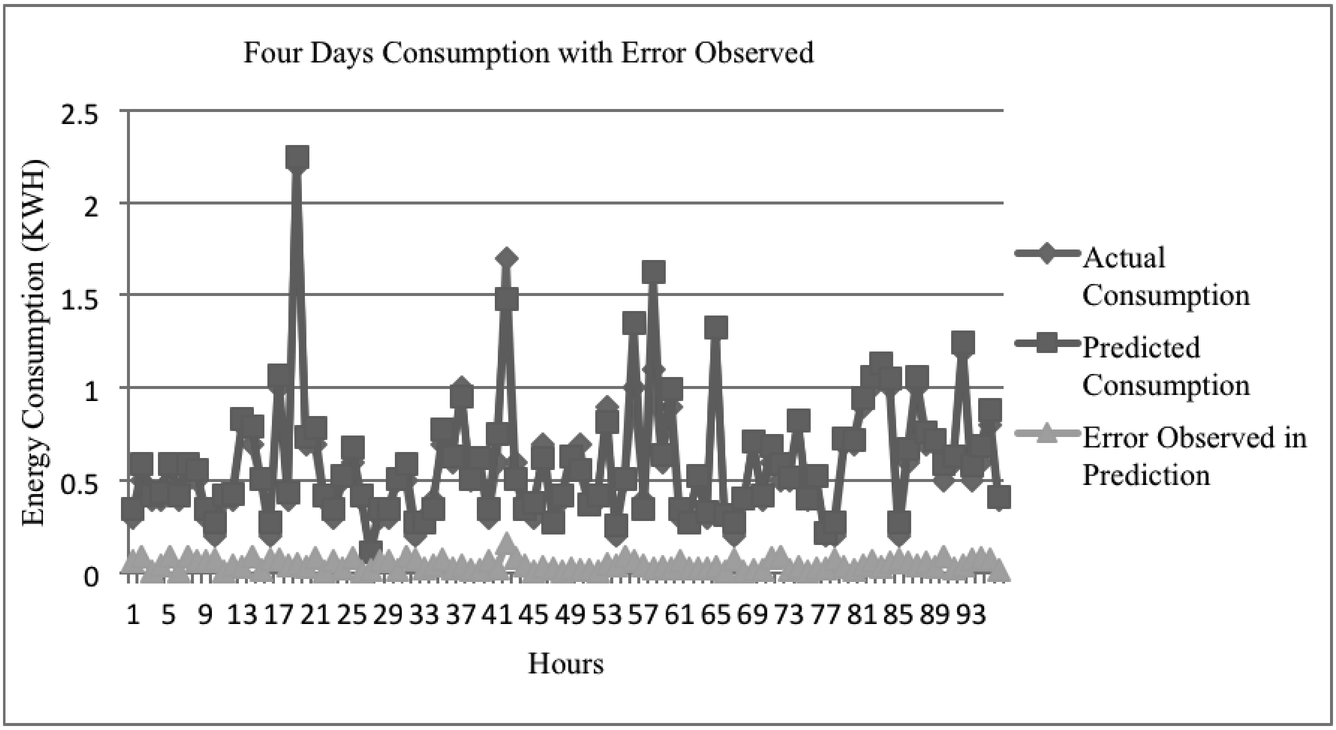

Fig. 9. The actual and predicted values of energy consumption of a single apartment during four days of the month with the error observed in prediction.

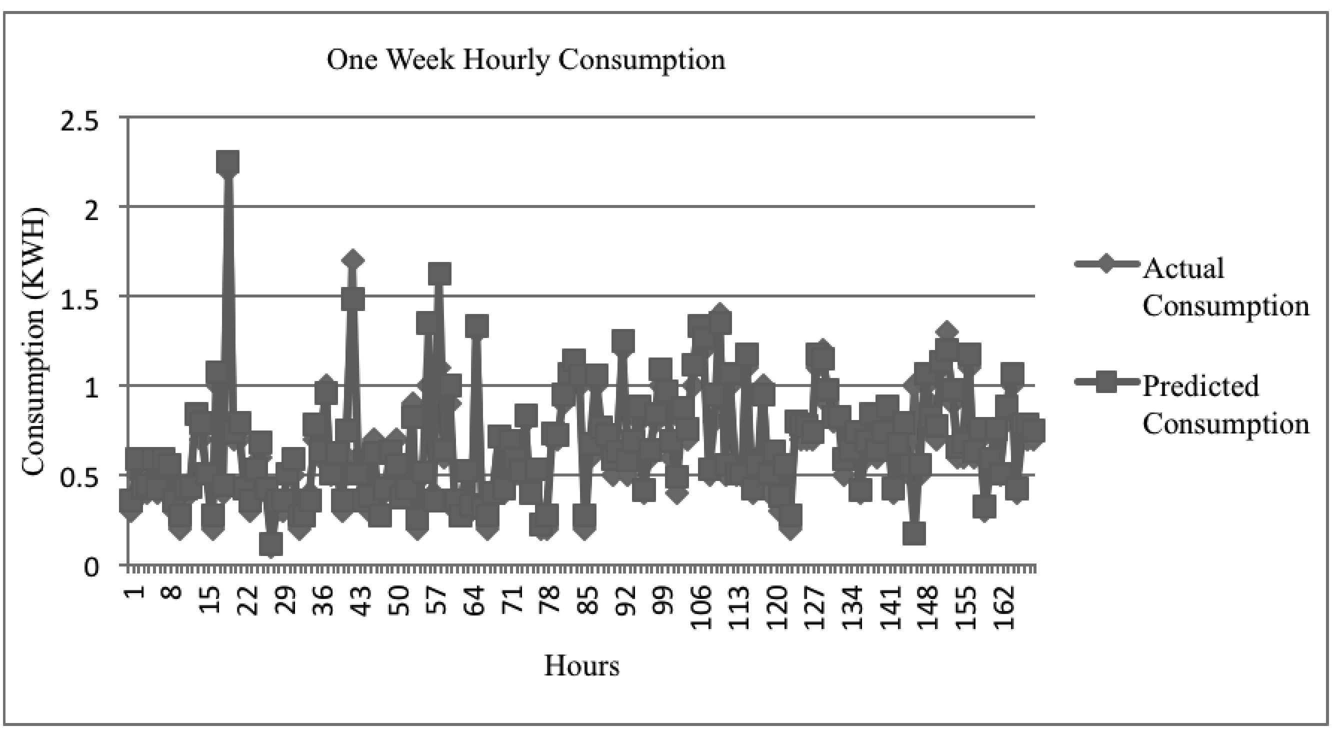

Fig. 10. The actual and predicted values of energy consumption of a single apartment during one week of the month

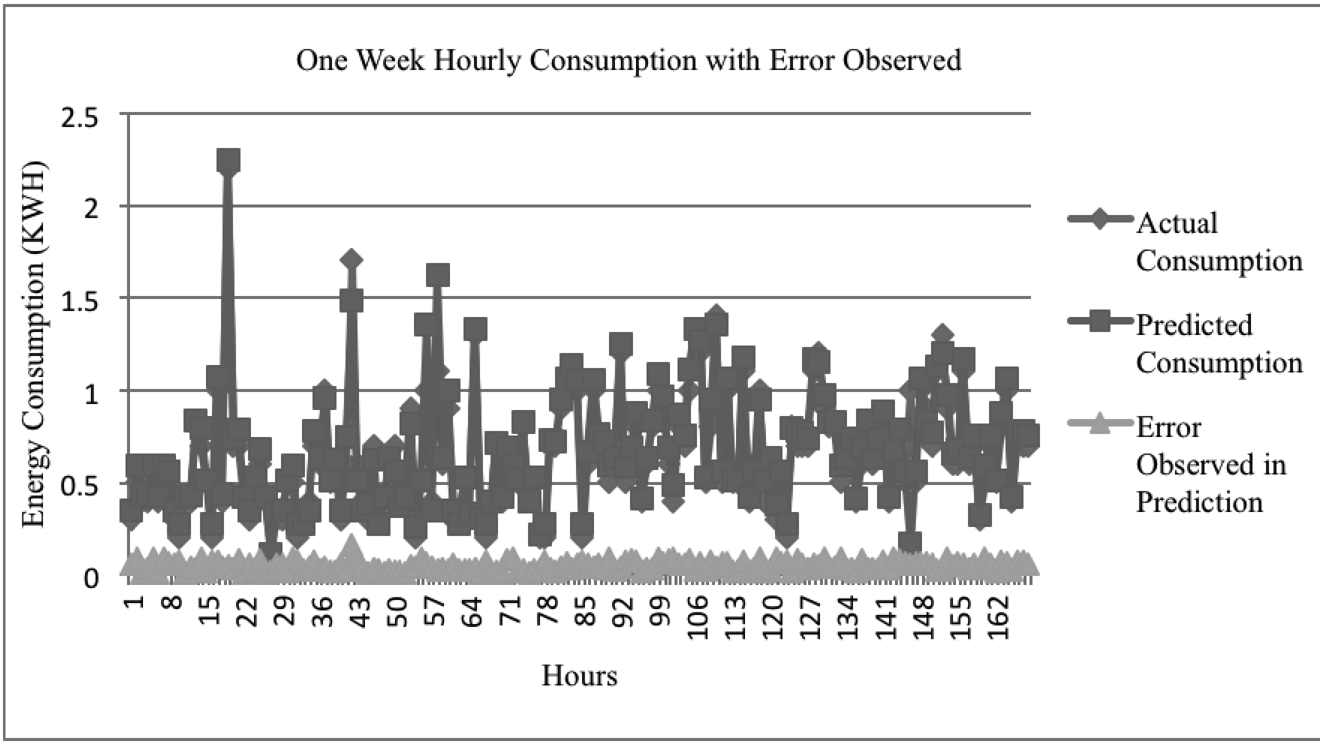

Fig. 11. The actual and predicted values of energy consumption of a single apartment during one week of the month with error observed in prediction

4. Conclusion

In this paper, we applied multi-layer perceptron to hourly energy consumption prediction. The multi-layer perceptrons were trained and tested using historical hourly consumed real data of twenty apartments in Seoul, Republic of Korea for the month of January 2010. The data were divided into 70% (9982 samples) training and 30% (4278 samples) testing. The performance of the models was assessed using mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE). The major findings of the study are summarized as follows:

- After trials and errors on different types of training algorithms, hidden layer transfer functions, output layer transfer functions and different number of neurons in the hidden layer a total run of 20 different architectures of multi-layer perceptron were tested.
- The best model was chosen using scaled conjugate gradient as training algorithm, tangent sigmoid as hidden layer transfer function, linear function as output layer function and total of 19 neurons in the hidden layer
- Differences in actual consumed power and predicted consumed power were very small for all observed samples during testing

Our method of testing different combinations of training functions, hidden layer functions, output layer functions and number of neurons in the hidden layer produce small prediction errors. Therefore, this method can be applied for different types of predictions keeping in consideration the results obtained for different combinations.

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التنبؤ باستهلاك الطاقة على المدى القصير في المباني السكنية الكورية بالاستخدام الأمثل للمستقبلات متعددة الطبقات

فضلي وحيد*، دو هيون كيم
قسم هندسة الحاسب الآلي، جامعة جيجو الوطنية، مدينة جيجو، كوريا الجنوبية،
*wahid_uomian@hotmail.com

خلاصة

يعتبر التنبؤ باستهلاك الطاقة المنزلية على المدى القصير ذو أهمية حيوية لتصميم وإدارة نظم إنتاج وتخزين الطاقة. في هذا البحث، نقدم منهجية التنبؤ باستهلاك الطاقة على المدى القصير بالاستخدام الأمثل للمستقبلات متعددة الطبقات. تم تطوير ما مجموعه 20 نموذج من بيرسيبترون متعدد الطبقات (MLP) مع الأبنية المختلفة للتنبؤ باستهلاك الطاقة لكل ساعة. لتحديد أفضل مزيج من خوارزميات التعلم ووظائف نقل الطبقات المخفية ووظائف طبقة المخرجات، فإنه تم النظر إلى أنواع مختلفة من خوارزميات التدريب والطبقة الخفية ووظائف طبقة المخرجات. تم استخدام اثنين من خوارزميات التدريب الرئيسية، وهي تدرج المكورات وخوارزمية ليفنبرج Levenberg-Marquardt للتضخم الخطي. في الطبقة المخفية، تم استخدام تقاطعات ومعادلات سينية ولوغاريتمية كوظائف للتنشيط، وتم استخدام اللوغاريتم السيني الخطي والتقاطع السيني كوظائف لدوال المخرجات. واستند تقييم أداء النماذج على متوسط الخطأ المطلق (MAE) ومتوسط مربع الخطأ (MSE) وجذر متوسط مربع الخطأ (RMSE). وتم اختبار أداء وجدوى النموذج المقترح على البيانات الحقيقية لبعض المباني السكنية في مدينة سيول في جمهورية كوريا لفترة محددة من الزمن. كان لدينا إجمالي بيانات عينات 14260 (20 شقة × 31 يوم × 23 ساعة) تم تقسيمها إلى 70٪ (9982 عينة) كتدريب و30٪ (4278 عينة) كاختبار.