Short-term Load Forecasting Model with Predicted Weather Data

ZHU Guangya[a], CHOW Tin-tai[b], Norman TSE[c]

[a] *City university of Hong Kong, Hong Kong SAR, zhuguangya828@yahoo.com*
[b] *City university of Hong Kong, Hong Kong SAR, bsttchow@cityu.edu.hk*
[c] *City university of Hong Kong, Hong Kong SAR, bsnorman@cityu.edu.hk*

ABSTRACT

Introduced in this paper are our recommended weather forecasting model and the associated prediction procedure. These facilitate the formulation of a convenient and accurate short term energy consumption forecasting method. We started with an overview of the building related energy forecasting. A simplified weather model was then proposed for the output of key weather data, including dry-bulb temperature, relative humidity and global solar radiation. On top of this, a framework of energy-use forecasting technique is introduced, which brings in the data filtering and raw data set regrouping methods. Our result comparisons show that the predictions of the Mean Absolute Percentage Error (MAPE) from the weather data on record, or from the model-generated data set, differ very little. Illustrating examples via a university building case are discussed. The above indicate that our proposed weather prediction model is convenient and suitable for the mentioned purposes. Comparisons among the different input data sets also demonstrate that the forecasting accuracy has been enhanced through input data filtering and regrouping.

Keywords: *weather prediction, energy consumption forecasting, energy saving*

1. INTRODUCTION

Global warming and fossil fuel depiction lead to international protocols formulation, that in turn drive the building owners, operators and customers to improve the overall system energy efficiency and to search for new technologies with better saving potential. Along this direction, an accurate short-term load prediction tool is mostly in need. It is crucial for the operation plan of the utility systems and for the smart micro-grid applications as well, to allow the utility to take action, or to balance the supply and demand side(s) in principle, or to reduce the overall energy consumption.

Generally speaking, energy consumption forecasting methods can be grouped into three categories based on their time-horizon [Gonzalez-Romera E, 2006], i.e. long-term forecasts of more than one year, medium-term load forecasts from one week ahead to one-year ahead, and short-term load forecasts (STLF) used for predicting the load from a few hours up to weeks ahead. Among these, STLF with the time-horizon of 24-hour ahead is often focused on [Borges CE et al., 2013]. Accurate STLF of the micro-grid can enhance the system ability to use renewable energy resources and to improve the system efficiency and economics in response to the electricity markets [Massana J et al., 2015]. This will enable the utility provider to take action to control the balance between the supply and demand sides. However, there are many influential factors like the weather conditions of tomorrow that affect the building operation and make the building electricity load more difficult to predict. Many researchers worked on the sensitivity of these factors and introduced various black-box or grey-box forecasting models [Chitsaz H et al., 2015 and Chae YT et al., 2016]. Many external factors employed were actually the weather data on record of the following hours instead of truly acquired from weather forecast. In view of this, some researchers [Friedrich L et al., 2015, Roldan-Blay C et al., 2013 and Lazos D et al., 2015] propose to use the weather forecast data from third party institutions, or using a forecasting model to generate the unknown weather data. However, this kind of data is not always available and often has cost implication. It becomes worthwhile to develop new weather forecast methodology for acquiring the unknown weather data set (or the next day 24-hour weather profile) for STLF applications.

2. WEATHER FORECAST MODEL

The new weather forecasting model here introduced serves to generate predicted weather data of tomorrow simply based on the publicly available weather forecast information, like those from internet. A generated sample of the discrete 24-hour dry-bulb temperature and relative humidity are shown in Figure1(a), and the predicted horizontal global solar radiation curve is in Figure1(b).

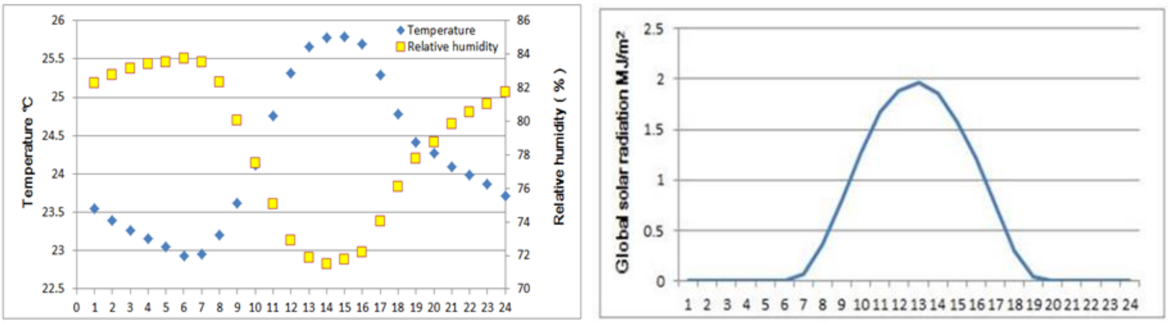


Figure 1: Generation of predicted weather data for the next day 24-hour profile

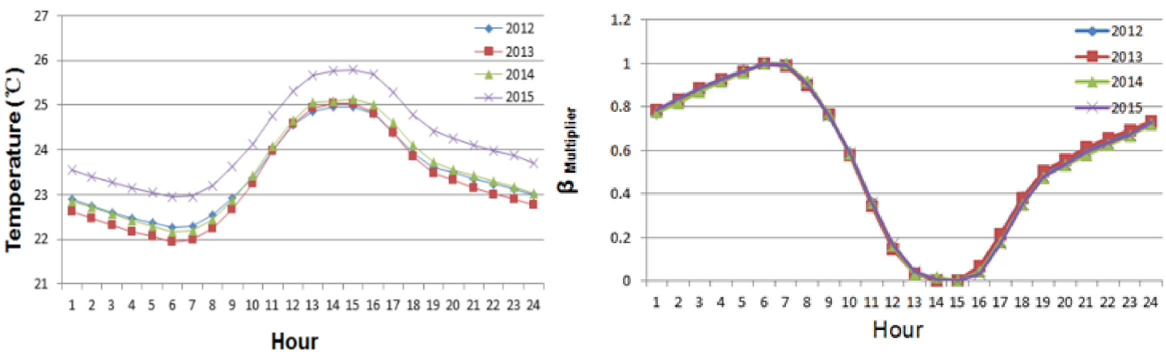
2.1 Dry-bulb temperature prediction

The dry-bulb temperature profile across the day embraces the range between its maximum and minimum values, T_{max} and T_{min}. It disseminates regular pattern geographically that can be approximated by the use of a daily range of multipliers, each of which provides the deviation ratio between T_{max} and that of the given hour $T_{current}$. Hence,

$$\mathrm{T_{current}} = \mathrm{T_{max}} - \beta_{Multiplier} \times (\mathrm{T_{max}} - \mathrm{T_{min}})$$

Equation 1

The range of multiplier values $\beta_{Multiplier}$ can be generated from the historical weather record. For example, based on the Hong Kong Observatory weather data record from 2012 to 2015, the average daily temperature profiles are shown in Figure 2(a), and the multiplier values generated are shown in Figure 2(b). It can be seen that the multiplier values across the day are more or less the same for these 4 years although 2015 was actually much warmer than the other 3 years.



(a) Average daily temperature profile (b) Multiplier value profile

Figure 2: Averaged hourly weather data profiles: (a) Daily temperature, and (b) Multiplier value

2.2 Relative humidity prediction

Based on the predicted temperature value and its relationship with the water vapour saturation pressure, the relative humidity (RH or φ) can be determined.

Step 1: Calculate water vapour saturation pressure

$$p_{qb} = 610 \times 10^{\frac{7.45T}{235+T}}$$

Equation 2

where p_{qb} is the water vapour saturation pressure and T is the temperature.

Step 2: Generate reference water vapour pressure P_c

The RH of the daytime and night-time can be acquired from local weather forecasting report. Since Hong Kong is a coastal city, P_c is relatively stable within a day. Then the constant value of P_c can be taken as the average of the daytime and night-time RH.

Step 3: Calculate relative humidity (RH)

$$\varphi = \frac{\mathrm{P}_c}{p_{qb}} \times 100\%$$

Equation 3

2.3 Global solar radiation prediction

In order to predict the global solar radiation for the next day 24 hours, the sunrise time (t_{sr}) and the sunset time (t_{ss}) on the day of prediction are first calculated [Roldan-Blay C et al., 2013).]. d_n denotes the day number of the year from 1 to 365, taking February 29 the same as February 28. Thus, the daily angle θ is calculated as:

$$\theta = \frac{2\pi}{365}(d_n - 1)$$

Equation 4

The equation of time (et) denotes the difference between the true solar time and the mean solar time, in that

$$\mathrm{et} = (0.000075 + 0.001868\cos(\theta) + 0.032077\sin(\theta) - 0.014615\cos(2\theta) - 0.04089\sin(2\theta))229.18$$

Equation 5

Solar declination δ is the angle in radians between the equatorial plane and the line connecting the centre of the sun and the earth. It can be shown that:

$$\delta = 23.45\cos(2\pi\frac{d_n - 173}{365})\frac{\pi}{180}$$

Equation 6

The solar angular hour (h) is calculated as:

$$\mathrm{h} = \cos^{-1}\left(\frac{\sin\left(\frac{-0.833\pi}{180}\right)\sin(\delta)}{\cos(\varphi)\cos(\delta)}\right)$$

Equation 7

The number of hours of daylight (n_d) is a function of h, in that

$$\mathrm{n}_d = \frac{h}{7.5}\frac{180}{\pi}$$

Equation 8

Then the sunrise (t_{sr}) and sunset time (t_{ss}) are:

$$\mathrm{t}_{sr} = 12 - \frac{nd}{2} - \frac{et}{60}$$

Equation 9

$$\mathrm{t}_{ss} = 12 + \frac{nd}{2} - \frac{et}{60}$$

Equation 10

Finally, the solar radiation model can be based on the simple sky model [Iqbal, M 1983], which is characterised by the parameters of the peak solar irradiance (I_{max}), the sunrise time (t_{sr}) and the sunset time (t_{ss}).

2.4 Results of weather prediction

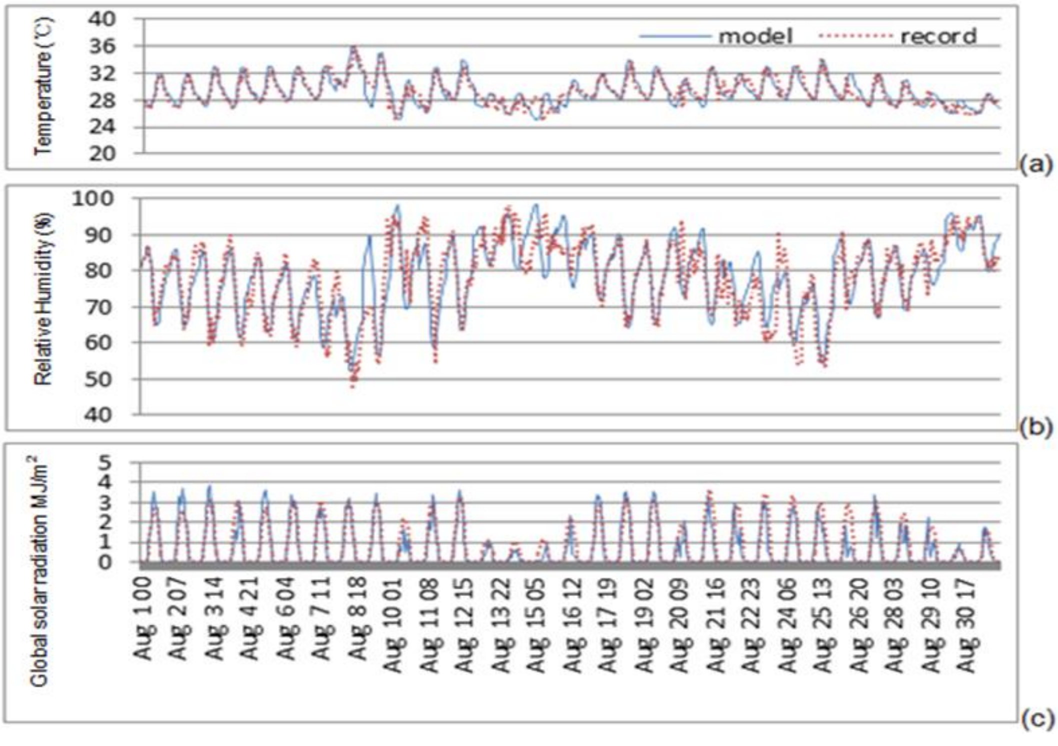


Figure 3: Results comparisons: (a) Dry-bulb temperature (b) Relative Humidity, and (c) Horizontal global solar radiation

The deviations of weather data between our proposed model and the record data from 2013 were determined. The comparison results of temperature, relative humidity and global solar radiation in January are shown in Figure 3 (a) to (c). The overall forecasting mean absolute percentage error (MAPE) of dry-bulb temperature, relative humidity and global solar radiation are 3.2245, 5.6978 and 11.3064 respectively. This indicates that the proposed model is able to give predictions with good accuracy.

3. FORECASTING METHODOLOGY

In the forecasting framework, the raw data is first prepared. Then the influence factors are ranked by their importance, and the less important factors will be filtered. Then the remaining input data are regrouped based on their building energy consumption characteristics. Once the filtering and regrouping processes are completed, the forecasting model structure is subject to optimization. The following shows its application to an illustrating case.

3.1. The study case

The presented case is a university building having an overall floor area of 70,000 m^2 and is a two northwest-oriented blocks each with seven floors. The daily operation hours are from 07:00 - 23:00 on workdays and 07:00 - 18:00 during weekend. Space cooling is required throughout the year. ANN is adopted as the forecasting model, with the LSSVM applied as a reference model [Hyun Chul Jung et al., 2015]. These two models program was developed in MATLAB 2015a version, running on the computer with 32G memory and 2.67GHz process. The test period was from July to September 2014. The rest of data was used as the training sample.

3.2. Data preparation and filtering

The 2013- 2014 weather data, historical energy consumption record, and building operation schedule were used as input parameters to predict the next day 24-hour energy consumption. The weather data include dry-bulb temperature, relative humidity, global solar radiation, rainfall, clearness of sky, cloud condition and wind speed. The historical energy consumption record was from the building management system. The operation schedule information was based on the day types, hours of the day and the periods of the whole academic year. These include the semester, student revision period, examination period, and semester break - all are in the university academic calendar.

The input data were filtered before loading into the forecasting model. The test was by means of the mutual information (MI) criterion, in that the influence factors were collected with the MI value calculated, and then their importance were ranked [Keynia F, 2012 and Esmaeili S et al., 2014].

3.3. Data regrouping

Figure4 shows the energy consumption contour of this building, through which the overall daily profile and weekly trend can be readily visualized. The X-axis shows the dates in August and the Y-axis is the 24-hour across the day. It can be seen that from 00:00 AM to 8:00 AM, the energy consumption is low. Then after 8:00 AM, the energy consumption is increasing rapidly. The peak load occurs between 14:00 PM and 17:00 PM. After 20:00 PM, the energy consumption is decreasing. On the other hand, the daily consumption during weekday is relatively stable. Those during weekend are comparatively low. But there are exceptions. For instance, because of the typhoon on August 14, the consumption was low throughout this weekday. In our model, the energy consumption forecasting on holidays or under special circumstances were handled separately. Accordingly, the input data are divided into two parts. One part includes only the normal working day information, as data set 1. The rest consists of the holidays, weekends and days with emergency; the information are referred as data set 2.

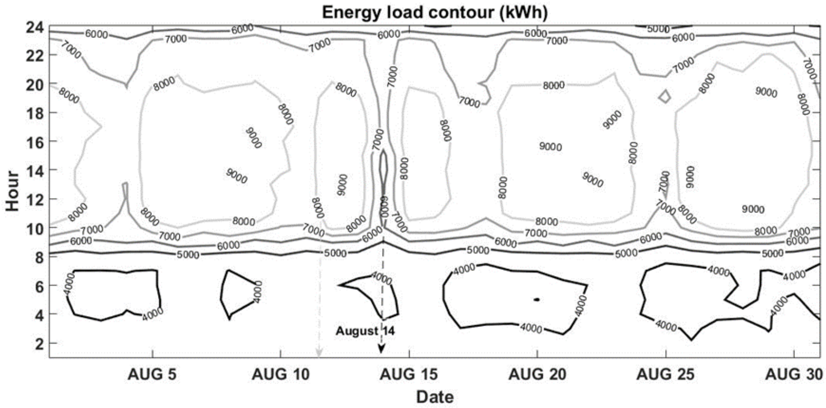


Figure 4: Hourly energy consumption contour

4. FORECASTING RESULTS

The details of forecasting accuracy can be found in Tables 1 to 3. The accuracy criteria adopted are the Mean Absolute Percentage Error (MAPE), Daily Peak MAPE, Coefficient of Variance of the Root Mean Squared Error (CVRMSE) under 95% confidence limits.

The results of forecasting are found agreeing well with the real consumption load. The overall MAPE values are found similar by using either the record weather data or the proposed weather forecast data. The simulation results are also compared with different input data sets, such as those without filtering or regrouping. The results indicate that filtering and regrouping are the effective ways to improve the forecasting accuracy. Figure 5 is the energy consumption profile comparison between the two different forecasting models and the actual load curve. The black solid line represents the real electrical consumption, while the red and blue broken lines represent the ANN and LSSVM forecasting energy profiles respectively. The comparison confirms that the forecasting results agree well with the real consumption load. The overall MAPE are no more than 6.1% and 5.5% for the ANN model and the LSSVM model respectively.

Model	record weather data			modelled weather data		
	MAPE	Daily peak MAPE	CVRMSE	MAPE	Daily peak MAPE	CVRMSE
ANN	5.9775	4.9217	7.9112	6.0245	5.2247	8.1223
LSSVM	5.2496	4.1713	8.0707	5.4432	4.5712	8.3210

Table 1: Comparison of forecasting errors between real and modelled weather data

ANN	Filter			No filter		
	MAPE	Daily peak MAPE	CVRMSE	MAPE	Daily peak MAPE	CVRMSE
Data set1	4.9695	3.8383	4.1505	5.3045	4.0335	7.3465
Data set2	7.0423	6.0807	9.4196	7.4061	6.7266	9.8304

Table 2: Forecasting errors with input data filtered and without filter (ANN vs real data)

Model	regroup			no regroup		
	MAPE	Daily peak MAPE	CVRMSE	MAPE	Daily peak MAPE	CVRMSE
ANN	5.9775	4.9217	7.9112	6.8615	6.6017	9.4473
LSSVM	5.2496	4.1713	8.0707	5.7847	4.2815	8.3282

Table 3: Overall forecasting errors between input data with and without regrouping (Real weather data)

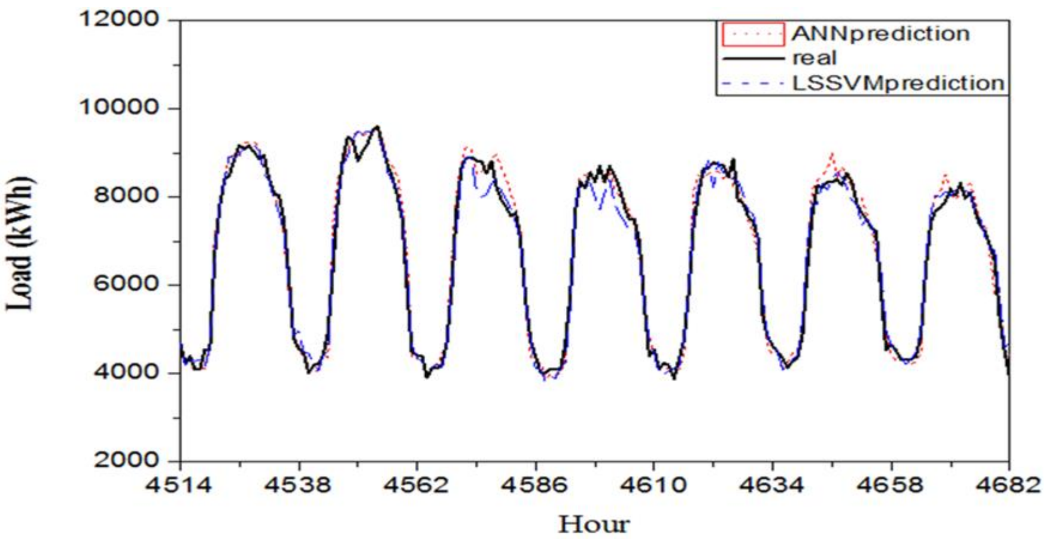


Figure 5: Forecasting results vs. real energy consumption in the case study

5. CONCLUSION

A new method is proposed to generate weather data by prediction based on information publicly available. Data of influence factors were carefully collected. The importance of different input data was analysed with the application of mutual information in a study case. The proposed method has been shown able to achieve good forecasting results for the next day 24-hours energy consumption. The comparison of forecasting results shows that by regrouping and filtering the input data, the forecasting accuracy can be improved. It is also confirmed that the weather prediction model here proposed is convenient, and suitable for short-term load forecasts of buildings.

ACKNOWLEDGEMENT

The work described in this article was financially supported by the Contract Research Grants of the City University of Hong Kong (Project no. 9231136).

REFERENCES

[1] Borges C.E., Penya Y.K., Fernández I., Prieto J. and Bretos O. (2013) “Assessing tolerance-based robust short-term load forecasting in buildings” Energies 6(4): 2110-2129.
[2] Chae Y.T., et al. (2016) "Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings" Energy and Buildings 111: 184-194.
[3] Chitsaz H., et al. (2015) "Short-term electricity load forecasting of buildings in micro grids" Energy and Buildings 99: 50-60.
[4] Esmaeili, S., et al. (2014) "Development of a thermal and electrical energy management in residential building micro-grid." Journal of Renewable and Sustainable Energy, online publication 1-Jan-2014.
[5] Friedrich L. and Afshari A. (2015) "Short-term forecasting of the Abu Dhabi electricity load using multiple weather variables" Energy Procedia (ICAE 2015) 75: 3014-3026.
[6] Gonzalez-Romera E., Jaramillo-Moran M.A. and Carmona-Fernandez D. (2006) “Monthly electric energy demand forecasting based on trend extraction” IEEE Transactions on Power Systems 21(4): 1946-1953.
[7] Hyun Chul Jung, Jin Sung Kim, Hoon Heo. (2015) “Prediction of building energy consumption using an improved real coded genetic algorithm based least squares support vector machine approach” Energy and Buildings 90: 76–84.
[8] Iqbal M. (1983) An Introduction to Solar Radiation; Elsevier: New York, NY, USA.
[9] Keynia, F. (2012) "A new feature selection algorithm and composite neural network for electricity price forecasting" Engineering Applications of Artificial Intelligence 25(8): 1687-1697.
[10] Lazos, D., et al. (2015) "Development of hybrid numerical and statistical short term horizon weather prediction models for building energy management optimisation" Building and Environment 90: 82-95.
[11] Massana J., et al. (2015) "Short-term load forecasting in a non-residential building contrasting models and attributes" Energy and Buildings 92: 322-330.
[12] Roldan-Blay, C., et al. (2013). "Upgrade of an artificial neural network prediction method for electrical consumption forecasting using an hourly temperature curve model" Energy and Buildings 60: 38-46.