Applied Energy Symposium 2019: Low carbon cities and urban energy systems
October 16-18, 2019, Xiamen, China
Paper ID: 0067

FORECASTING ANNUAL ELECTRICITY CONSUMPTION OF OFFICE BUILDINGS USING A MODIFIED GREY INTERVAL MODEL

Yibo Chen [1*], Jianzhong Yang [1], Umberto Berardi [2]

1 School of Civil Engineering, Zhengzhou University, Zhengzhou, 450000, China (Corresponding Author)

2 Faculty of Engineering and Architectural Science, Ryerson University, 325 Church Street, Toronto, Canada

ABSTRACT

A reliable prediction of energy consumption is crucial for a reasonable building energy management. Considering the uncertain principles of annual electricity consumption with limited datasets, a modified grey interval prediction model abbreviated as BOGIM(1,1) is proposed in this paper. Firstly, the changing patterns of annual series were detected, in order to lower the uncertainty. Afterwards, the predicted intervals were obtained with modified BOGIM(1,1), in which various weakening and enhancing buffer operators were added simulate different future operation scenarios. Finally, the adaptability of this model is summarized based on recognized patterns and predicted accuracy. Specifically, 92 office buildings in Beijing of China were adopted to test the BOGIM(1,1) model. Results show that this proposed model outperforms the traditional GM(1,1) by improving the prediction accuracy for almost 90% of the buildings up to 18.45%, and it is more applicable for target-oriented energy policies.

Keywords: annual electricity consumption, interval prediction, office buildings, grey model, buffer operator.

NONMENCLATURE

Abbreviations	
GM	Grey model
BOGIM	Grey interval model combined with buffer operators
AECIB	Annual energy consumption of individual buildings

Symbols	
n	Year
$\gamma(t)$	The capacitable scope of step ratio
$xd(k)$	First order enhancing buffer operator
$xd^2(k)$	Second order enhancing buffer operator

1. INTRODUCTION

Along with the increasing pressure for energy and energy security, policies in China have been shifting towards the simultaneous control of both the energy intensity and the total amount of energy demand. As one of the major contributors to the overall, the building sector has captured increasing attentions in recent years in China as well as in many other countries [1]. In order to facilitate the energy management for individual buildings, a reliable prediction of energy consumption must be taken as the crucial basis.

Current prediction models for energy consumption can be categorized into three types: regression model, intelligent model and time series model [2]. In previous studies [3-5], the regression and intelligent models to manage the hourly energy prediction and energy benchmarks for classified buildings have been discussed in details. However, for annual energy consumption of individual buildings (AECIB), these proposed models are not applicable, due to the limited access to data and unsatisfied data quality. Under such circumstances, the grey model, which was proposed firstly by Deng [6-7], has been adopted to predict the electricity energy consumption, renewable energy, traffic vehicles etc., owing to its powerful modeling ability with limited datasets of not less than 4 points. Among the grey

Selection and peer-review under responsibility of the scientific committee of CUE2019

models, the GM(1,1) model is the most popular one [6]. Although this model has been modified in terms of initial conditions and the principle of new information priority [8], the optimal system parameters [9], the hybrid type combined with other algorithms [10] etc., it cannot always provide satisfactory prediction when faced with volatility sequences in practical applications [11].

The AECIB is influenced by various factors, such as occupancy rates, management levels etc.. Therefore, a accurate prediction model should consider not only the historical changing inertia, but also the future developing scenarios. To tackle this uncertain problem with limited datasets, a modified grey interval model combined with weakening and enhanced buffer operators, referred to as BOGIM(1,1), is proposed to make a compromise between historical changing principles and future developing scenarios.

2. METHODOLOGY

As addressed by Deng [7], the grey theory was developed especially focusing on problems with clear extension and unclear connotation, on the basis of poor information. Accordingly, the AECIB has features of short sequence length, limited access to related factors, different changing tendencies (unclear connotation), and restricted changing sections (clear extension). Thus, it can be concluded that the grey theory is appropriate for predicting the annual energy consumption of buildings.

In this paper, based on the data-driven modeling theory, the temporal features and changing patterns of annual energy consumption was firstly recognized, followed by a modified data-driven BOGIM(1,1) model. Finally, the applicable evaluation of this BOGIM(1,1) is summarized with the recognized patterns and the analysis of prediction accuracy.

2.1 Pattern recognition of annual sequences

The changing patterns and fluctuating scopes of annual energy consumption sequences could be quite various among different individual buildings for a certain building typology. This circumstance is determined mainly by different building characteristics and operation. As a result, the pattern recognition of annual time series should be taken as the first step.

The changing patterns of AECIB could be divided into three types: monotone increasing, monotone decreasing, and fluctuating. In this paper, the grey correlation analysis, which estimates the relevance via the similarity level of geometrical shapes [6], was applied to recognize different patterns. Compared with the clustering or other correlation analysis, the grey correlation analysis has no special requirements of data volume, and it can guarantee the consistency between quantified results and qualitative analysis at the same time. In this paper, the grey correlation analysis was conducted to evaluate the distance of corresponding points between the sequence to be predicted and the pre-setting benchmarked sequence.

Particularly, the benchmarked sequence is labeled as $X_0 = \{x_0(k) | k = 1, 2, \cdots, n\}$, and the sequence to be predicted is labeled as $X_i = \{x_i(k) | k = 1, 2, \cdots, n\}$. In this way, the sequences of X_0 and X_i can be regarded as two points in a n-dimensional space, in which the relevant level is evaluated by the distance *d*(X_0 , X_i) between these two points.

In order to recognize different changing patterns, the benchmarked sequences was set as shown in Eq. (1), in which $X_{0\text{-}0}$ represents stable patterns, sequences of $X_{0\text{-}I+} \sim X_{0\text{-}IV+}$ represent patterns with different increasing ranges, sequences of $X_{0\text{-}I-} \sim X_{0\text{-}IV-}$ represent patterns with different decreasing ranges.

$$X_0 = \begin{bmatrix} x_{0-0} \\ x_{0-I+} \\ x_{0-II+} \\ x_{0-III+} \\ x_{0-IV+} \\ x_{0-I-} \\ x_{0-II-} \\ x_{0-III-} \\ x_{0-IV-} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1.05 & 1.1 & 1.15 & 1.2 \\ 1 & 1.1 & 1.2 & 1.3 & 1.4 \\ 1 & 1.15 & 1.3 & 1.45 & 1.6 \\ 1 & 1.2 & 1.4 & 1.6 & 1.8 \\ 1 & 0.95 & 0.9 & 0.85 & 0.8 \\ 1 & 0.9 & 0.8 & 0.7 & 0.6 \\ 1 & 0.85 & 0.7 & 0.55 & 0.4 \\ 1 & 0.8 & 0.6 & 0.4 & 0.2 \end{bmatrix} \qquad (1)$$

2.2 Modified BOGIM(1,1)

Due to the general uncertainty of future scenarios, the interval prediction, especially when detailed operation strategies are absent, is more applicable for the target-oriented energy policies. The limitation of existing studies can be concluded as follows.

- Previous grey interval models are developed with the help of residual correction [12]. There are two main requirements: grouping by plus or minus of the residuals, and a minimum data volume of 4 within the same group. As a result, the data volume for current interval prediction should not be smaller than 8. However, most of the current monitoring platforms cannot provide a continuous sequence of annual energy consumption for 8 years.

- Traditional GM(1,1) is more appropriate for sequences with monotonous tendencies, rather than the sequences with fluctuating principles [7]. Moreover, most of the modified grey models are often discussed based on a specific sequence, which cannot support a convictive applicable conclusion.

Accordingly, with the help of buffer operators, a new grey interval model was proposed in this paper (Fig. 1) to predict the annual energy consumption. On the one hand, the required dataset of this modified BOGIM(1,1) model is the minimum points of 4. On the other hand, the prediction result could be more reliable together with the hypothetical scenario.

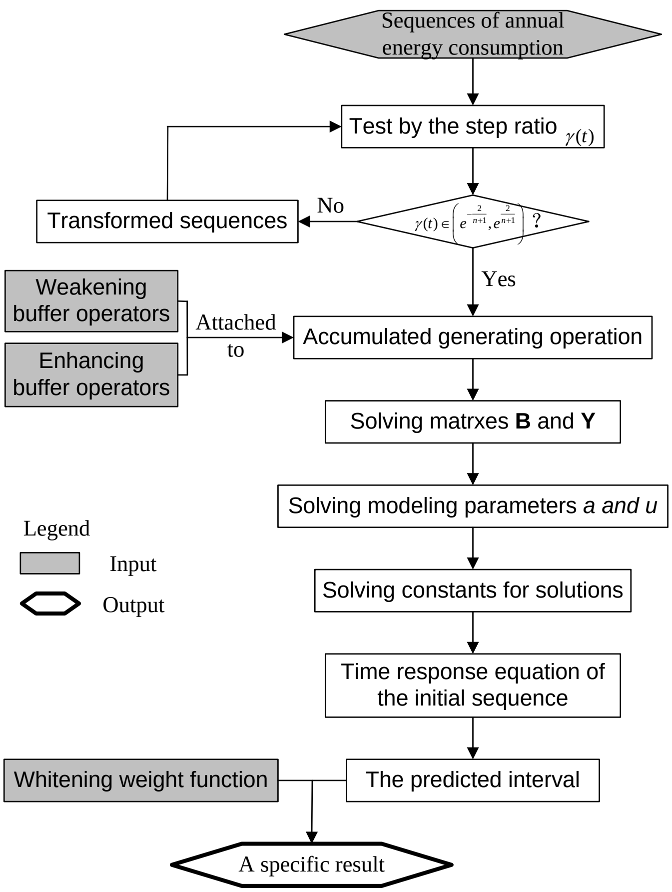

Fig 1 Flow chart of the proposed BOGIM(1,1) model

As shown in Fig. 1, the accessional buffer operators [6] are utilized to simulate different scenarios. Afterwards, the whitening weight function is applied to quantify the influence of operation strategies. Thus, a specific prediction result can be obtained.

For a random sequence X=(x(1), x(2),..., x(n)), the buffer sequence XD=(xd(1),xd(2),..., xd(n)) could be obtained after subjoining a sequential operator D. Different sequential operators represent the enhancing or weakening functions of historical changing tendencies. In this way, the future developing scenarios are simulated. For example, the enhancing buffer operator can promote the increasing or decreasing rates. This can be the developing scenarios when the occupancy rates are not stable. Besides, with the help of buffer operators, the influence from a single abnormal value can also be reduced.

In this paper, the first order and second order average weakening and enhancing buffer operators are established. The first order and the second order enhancing buffer operators are given in Eq. (2).

$$\begin{cases} xd(k) = \dfrac{(n-k+1)x^2(k)}{\sum_{i=k}^{n} x(i)}, k=1,2,\cdots n \\ xd^2(k) = \dfrac{(n-k+1)(xd(k))^2}{\sum_{i=k}^{n} xd(i)}, k=1,2,\cdots n \end{cases} \tag{2}$$

2.3 Performance evaluation criteria

When carrying out the evaluation, predicted results are evaluated by relative error (RE) calculated according to Eq. (3), with the predicted point E_{pi} and the corresponding measured point E_{mi}.

$$RE(\%) = \left(E_{mi} - E_{pi}\right) / E_{mi} \times 100\% \tag{3}$$

3. DATA CHARACTERISTICS

Sequences of annual electric consumption intensity from 2011 to 2016 for 92 office buildings are given in Fig. 2, arranged according to the value in 2016 from low to high.

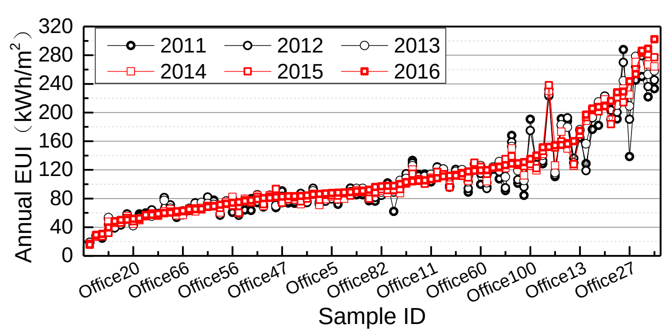

Fig 2 The annual electric energy intensity of 92 office buildings in Beijing of China

Two features can be observed as follows.

- Changing ranges can be quite different for individual buildings of the same kind. By statistics, the median of changing ranges is 14.52 kWh/(m^2•a), and the interquartile range is assessed as [9.07, 28.80] kWh/(m^2•a).
- Fluctuating features can also be quite different. In summary, the changing tendencies consist of monotonically increase, monotonically decrease and fluctuating. Moreover, the appearance orders and distances of up and down are also various for the fluctuating.

This proposed BOGIM(1,1) model is applied to these 92 sequences including various changing tendencies.

4. RESULTS AND DISCUSSION

4.1 Results of correlative degree

With the grey correlation analysis, the correlative degrees between all samples and the benchmarked sequences in Eq. (1) can be summarized in Fig. 3.

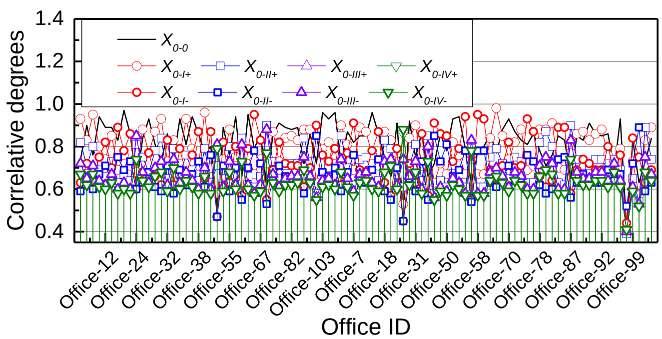

Fig 3 Summary of the correlative degrees of all samples

Taking Office-1 as an example, the correlative degrees with the benchmarked sequence are assessed as 0.74, 0.93, 0.82, 0.72, 0.67, 0.63, 0.59, 0.72 and 0.67. Thus this sample is classified into the $X_{0\text{-}I+}$ group, with the highest correlative degree of 0.93. In this way, the developing patterns of all samples can be recognized, when the operation information is absent. Thus, the uncertainty of annual prediction could be reduced.

4.2 Predicted results

In this paper, the sequence to be predicted has 5 data points from 2011 to 2015 (which means n=5). Therefore, the capacitable scope of step ratio can be calculated in Eq. (4). At the same time, the data points in 2016 are left for results evaluation. Specifically, values in 2016 within this scope are predicted directly by the proposed BOGIM(1,1) model, and other sequences should be transformed before prediction until the step ratios meet the capacitable scope.

$$\gamma(t)=\frac{x^0(t-1)}{x^0(t)}\in\left(e^{-\frac{2}{n+1}},e^{\frac{2}{n+1}}\right)=(0.7165,1.3956) \quad (4)$$

The predicted intervals, the measured data and the development coefficients of time response functions are summarized in Fig. 4, arranged according to the floor levels of intervals from low to high.

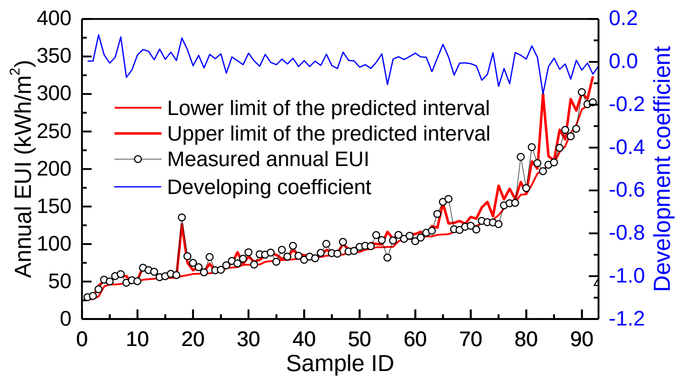

Fig 4 Summary of the predicted intervals, the measured data and the development coefficients of all samples

It can be observed as follows.

- Most of the measured points in 2016 are within or around the predicted intervals.
- The changing scopes of predicted intervals are relatively stable. The interquartile range of the intervals is assessed as [3.32， 13.49].
- The scope of absolute values of developing coefficients is [0.00049, 0.15], which is smaller than 0.3. Thus, these models can be used for multistep prediction [7].

4.3 Comparison with GM(1,1) and discussion

In order to give a further evaluation of this proposed model, the predicted results of BOGIM(1,1) are compared with those of the traditional GM(1,1) by relative errors in Fig. 5. Initial conclusions can be illustrated as follows.

- With this proposed BOGIM(1,1) model, the prediction accuracy of 88.04% samples is improved. The improved scope of prediction accuracy is assessed as 0-18.45%.
- The median of REs is -1.21%, and the interquartile range is [-4.54%, 0.12%]. It can be concluded that most samples can achieve good prediction accuracy.
- Among samples with REs larger than 10%, which occupies 7.78% of all, Office-37 has the highest RE of 23.83%. The sequence to be predicted of Office-37 is [129.59 135.96 129.77

127.83], and the measured data in 2016 is 160.01. It is obvious that the saltation of the value in 2016 attributes to the higher RE. Thus it can be concluded that this model is limited when dealing with saltation series.

- Among samples with step ratios outside the capacitable scope, the sequence to be predicted of Office-98 is [277.93 18.50 76.02 95.42], and the measured data in 2016 is 107.35. It can be observed that the value in 2011 is abnormal high, which may be caused by a storing or transmission mistake. However, with this BOGIM(1,1) model, it can reach a high prediction accuracy of 98.11%. This shows the fault-tolerant ability of this model.

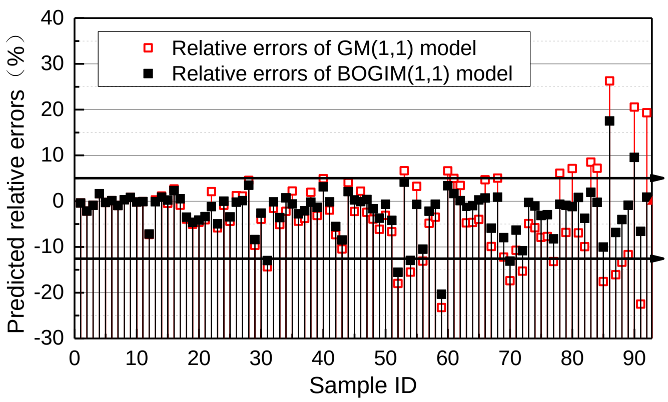

Fig 5 Comparison of relative errors between the proposed BOGIM(1,1) and the traditional GM(1,1)

Consequently, it can be concluded that the proposed BOGIM(1,1) can achieve stable and accurate prediction accuracy comparing with the traditional GM(1,1). At the same time, the prediction performance is not satisfied when dealing with saltation sequences.

5. CONCLUSIONS

The annual energy consumption for an individual building is influenced by both the historical principle and the future developing scenarios. In order to tackle this uncertain prediction problem with limited datasets, a modified grey interval prediction model named BOGIM(1,1) is proposed in this paper with the help of accessional buffer operators. After applying to the annual sequences of 92 office buildings in Beijing, it can be concluded that the prediction accuracy of 88.04% samples is improved by 0-18.45%, when comparing with the traditional GM(1,1) model. As the same time, the fault-tolerant ability of this model was also tested by samples with abnormal data points.

In future studies, this BOGIM(1,1) model should be applied to other building types with various operation strategies, in order to further test its adaptability.

ACKNOWLEDGEMENT

The study was supported by the National Key R&D Program of China (Grant No. 2017YFC0704200).

REFERENCE

[1] Berardi U. A cross country comparison of building energy consumption and their trends. Resour Conserv Recy 2017, 123: 230-241.

[2] Wu L, Gao X, Xiao Y, Yang Y, Chen X. Using a novel multi-variable grey model to forecast the electricity consumption of Shandong Province in China. Energy 2018, 157: 327-335.

[3] Chen Y, Wu J. Distribution patterns of energy consumed in classified public buildings through the data mining process. Appl Energ 2018; 226: 240-251.

[4] Chen Y, Tan H, Berardi U. Day-ahead prediction of hourly electric demand in non-stationary operated commercial buildings: A clustering-based hybrid approach. Energ Build 2017; 148: 228-237.

[5] Chen Y, Tan H. Short-term prediction of electric demand in building sector via hybrid support vector regression. Appl Energ 2017; 204: 1363-1374.

[6] Deng J L. Control problems of grey systems. Syst Contr Lett 1982; 1(5): 288-294.

[7] Deng J L. Introduction to grey system theory. J Grey Syst 1989; 1(1): 1-24.

[8] Ding S, Hipel K W, Dang Y. Forecasting China's electricity consumption using a new grey prediction model. Energy 2018; 149: 314-328.

[9] Wu W, Ma X, Zeng B, Wang Y, Cai W. Forecasting short-term renewable energy consumption of China using a novel fractional nonlinear grey Bernoulli model. Renew Energ 140 (2019): 70-87.

[10] Lu S. Integrating heuristic time series with modified grey forecasting for renewable energy in Taiwan. Renew Energ 2019; 133: 1436-1444.

[11] Xu N, Dang Y, Gong Y. Novel grey prediction model with nonlinear optimized time response method for forecasting of electricity in China. Energy 2017; 118: 473-480.

[12] Bo Z, Guo C, Si-feng L. A novel interval grey prediction model considering uncertain information. J Frankl Inst 2013; 350 (10): 3400-3416.

