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Multi-model prediction and simulation of residential building energy in urban areas of Chongqing, South West China

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ABSTRACT

Energy simulation and prediction plays a vital role in energy policy and decision making. This study has been conducted to predict the future energy demand in the urban residential buildings of Chongqing a city in south west China. The comparative study adopts and compares the results of different demand models to improve estimation efficiency for future projections. A structured questionnaire survey was undertaken to collect primary household energy consumption data for inclusion in the annual energy consumption simulation model. An ANN model, two Grey models, a Regression model, a Polynomial model and a Polynomial regression model were used to forecast and compare demand. The precision of the models have been used statistical methods. The predicted results show that the total residential building energy and electricity consumption in urban areas of Chongqing is increasing rapidly. Based on MRPE (%) and the statistical tests, the study concluded that an ANN model is the most acceptable forecasting method of the six models. Hence, based on ANN model, urban residential building energy consumption will be at 1005×10^4 SCE and electricity consumption will be at 264.81×10^8 kW h in 2025 which is about three times and four times higher than that of the 2012, respectively.

1. Introduction

Energy is considered as a key factor and element of the national economy [1]. With the rapid development of the world economy, global energy consumption is increasing [2]. The use of different types of end use devices such as air conditioner and electric heaters, oven, washing machine, vacuum cleaner etc. are increasing in China with the growth of China's economy. In addition, un-insulated buildings and low efficiency end use devices, residential building energy consumption is increasing rapidly. Hence, the objective of this study was to predict the pattern and level of future building energy demand in urban residential areas resulting from rapid urbanization. However, the excessive production and misuse of energy has some negative impacts on the environment, which can restrict regional economic development.

For the past two decades, China has experienced a fast-paced growth of its economy and has been in a phase of rapid urbanization development [3]. In 2001 building energy consumption accounted for about 27.6% of the total energy consumption. It is projected that the energy consumption in buildings will increase by up to 35% by 2020 [4]. Total carbon emission and environmental pollution has significantly increased as result of building energy consumption. Nowadays all over the world, energy and environmental problems have become a public concern. China is taking steps to reduce the energy demands of new buildings by investigating new construction methods and the development of eco-communities and eco-cities [5].

Chongqing is an important growth center in South West China with a total area of 82,400 km^2 and a total population of 33 million. Around 17 million (51%) of the population is considered rural and the remaining 16 million (49%) is considered to be an urban population [6]. For the ongoing development of both the urban and rural regions of Chongqing, the government has given the city municipality status placing it directly under the control of the central government [7]. Chongqing may be considered as a development hub of west China. The energy consumption

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in Chongqing is increasing at a geometric rate in all sectors. Amongst these sectors the residential building sector energy consumption is remarkable. From 1987 to 2012 residential building energy consumption in Chongqing increased from 2998,500 tce to 6628,800 tce, which is 121.07%. In 2012, Chongqing residential building energy consumption was 8% of total energy consumption of Chongqing [8]. In summer, Chongqing is an extremely hot and humid region and there has been increasing demand of air conditioning equipment and heating requirement [9]. Air conditioning alone consumes around 23% Chongqing's total energy consumption [10].

Multi-model prediction was the selected as the approach to the comparative study of selecting a valid and accurate prediction model. A structured questionnaire was used to collect primary data, and energy intensities of various drivers were collected from literatures for the annual energy consumption simulation. In addition, secondary data about residential building energy consumption and other relevant socio-economic data were collected from China Statistical Yearbook 2000–2012, Energy statistical yearbook of China 2000–2012 and Chongqing Statistical Yearbook 2000–2012. Annual urban residential energy consumption in Chongqing was simulated by a stock turn-over model. The model implies various energy demand drivers such as total household, number of people per household, total population, electrification rate, and end-use appliances such as space cooling and heating, water heating, cooking, refrigeration, lighting, and the powering of a wide variety of appliances with their intensities within a specific region. Therefore, the study has been calculated the total energy consumption in urban areas of Chongqing by integrated all drivers, end-use technologies and their intensities. Then a number of models Artificial Neural Network (ANN) model, Grey model such as GM (1,1), DGM (2,1), Regression model, Polynomial model and a Polynomial regression model were used for forecasting and comparing the precision of the models.

2. Literature review

In the EU in 2004, residential building energy consumption was 37% of the total energy, higher than both the transport (32%) and the industrial sector (28%). Residential building energy consumption in the UK was 28% of total building energy consumption (39%), which is slightly larger than the EU figure, whilst Spanish residential building used only 15% of total final building energy consumption (23%) [11]. The EIA has analyzed and forecasted future building energy consumption trends in their International Energy Outlook. In the next 20 years, energy consumption for building services is expected to increase by 34% (overall increase in 20 years) with the average annual rate of 1.5%. By 2030, energy consumption in non-domestic and residential sectors will be 33% and 67%, respectively [12]. Governments should fund for residential and commercial buildings energy consumption analysis by sectors, building stock (location, type, age, area, etc.) and energy parameters such as fuels, end uses, consumption, expenditures, etc., for making a comprehensive database which is very important for future planning [13,14]. Electricity is an important type of energy and is highly used in residential building and other sectors. In China, it is estimated that residential building energy consumption accounts for one third of the total energy consumption [15]. Residential building energy consumption increases rapidly with the development of living standards, urbanization, economic development, people's income. Within the period 1996 to 2006, residential building energy consumption in China increased by 1.3 times and in 2006 residential building energy consumption in urban areas was 45% (0.255 billion tce) of the total energy consumption. Clearly residential building is an important sector for energy consumption and contributes a larger portion of the total energy consumption than other sectors of the economy [15,16].

Different types of models such as ANN, Polynomial, Grey models, ARMAX and others model have been used for analyzing and predicting energy consumption in residential building sector. It is very important to understand which the effective models for predicting and analyzing present and future energy consumption in different sectors. Recently Pao et al. proposed an improved Grey model to evaluate and forecast future energy consumption in different sectors including residential buildings and industrial sectors in China [17]. Huang et al. have developed a Grey-Markov prediction model to examine and predict the electric-power supply demand and load in China [18]. Artificial Neural Network (ANNs) models are effective tools for analyzing various time series models [19]. ANNs are universally accepted tools for approximation that can approximate a large class of function with higher accuracy [20]. ANN models have received a great deal of attention and have proved powerful computational tools to forecast energy loads [21]. ANN architecture presents more insights than other regression based models and the traditional polynomial model [22]. A stock turn-over model has been applied by Zhou [23] to simulate the total residential building energy consumption by considering various energy consumption drivers and factors (Eq. (1)). The stock turn-over model has also been applied by Hossain et al. [7] for forecasting rural residential building energy consumption in Chongqing by using various energy consumption drivers. Engineering and statistical methods can be used to forecast the building total energy consumption. Artificial intelligence models, including Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) are useful tools to predict the consumption of building energy with higher accuracy but require adequate historical data and complex estimation process [5].

According to previous studies mentioned above, most of them have used only one or two modeling method to compare and forecast future energy demand. It is very difficult to take decision for future prediction by comparing one or two model, because accuracy of the model is an important factor. For better prediction, comparison and get higher accuracy of prediction, it's important to predict and compare by several models. Therefore, the study has considered six popular models to compare and forecast future energy demand in Chongqing, China.

3. Methodology

3.1. Urban residential annual energy consumption simulation by stock turn-over modeling

Residential building energy provides various services related with household living including space cooling and heating, cooking, lighting, water heating, refrigeration, and the powering of other end use devices. According to the Zhou [23] and Hossain et al. [7], end use devices were divided into four groups by technologies and their intensities were 390, 260, 1385 and 323.93 kWh/household/year. These groups were space heating and cooling, lighting energy use, cooking and water heating and other (miscellaneous) end use devices, respectively. The intensities of these groups have been used in the stock turn-over model. In addition, Hossain et al. [7] modified Eq. (1) by adding the space heating and cooling requirements of Chongqing rural areas (Eq. (2)). Space heating and cooling requirements need to be considered as one important driver as well as other end use devices (for example, computer, TV, refrigerator, washing machine, dryer). The present study has modified Eq. (2) by adding this driver to simulate the total annual energy consumption in urban residential buildings in Chongqing. This leads to Eq. (3).

$$E_{CR} = \sum_{m}^{\text{OPTION}} \frac{P_m}{F_m} \times \left[\left(\sum_j S_{j,m} \times UEC_{j,m} + E_m \sum_{i}^{\text{OPTION}} L_{i,m} \times Ca_{i,m} \times H_{i,m} \right) + \sum_{K}^{\text{OPTION}} \left(CW_{m,k} + LK_{m,k} \right) \right] \quad (1)$$

where E_{CR} = energy consumption in specific region, m; m = locale type (*urban, rural*); F_m = number of persons per household (*family*) in locale m; P_m = population in locale m; j = type of appliance or end-use device; E_m = electrification rate in locale m; $S_{j,m}$ = penetration of device or appliance j in percent appliance owned by household (*values in excess of 100% would indicate more than one device per household on average*); i = types of lighting bulb (*fluorescent, incandescent*); $L_{i,m}$ = number of lighting bulb of type i per household in locale m; $Ca_{i,m}$ = power of bulb of type i in locale m; $H_{i,m}$ = hours of use of bulb of type i in locale m; UEC_j = energy intensity of appliance or device j in MJ or kW h/year; K = fuel type; $LK_{m,k}$ = Lighting energy use of fuel k in locale m in MJ/household/year; and $CW_{m,k}$ = cooking and water heating energy use of fuel k per household per year in locale m in MJ/household/year.

Including space heating, the modified equation can be written as;

$$E_{CR} = \sum_{m}^{\text{OPTION}} \frac{P_m}{F_m} \times \left[\left(\sum_j S_{j,m} \times UEC_{j,m} + E_m \sum_{i}^{\text{OPTION}} L_{i,m} \times Ca_{i,m} \times H_{i,m} \right) + \sum_{K}^{\text{OPTION}} \left(CW_{m,k} + LK_{m,k} + SH_{m,k} \right) \right] \quad (2)$$

where $SH_{m,k}$ = space heating and cooling energy use of fuel k in locale m in MJ/household/year.

In addition to other end use devices in Chongqing urban areas, the reconstructed equation can be written as;

$$E_{CR} = \sum_{m}^{\text{OPTION}} \frac{P_m}{F_m} \times \left[\left(\sum_j S_{j,m} \times UEC_{j,m} + E_m \sum_{i}^{\text{OPTION}} L_{i,m} \times Ca_{i,m} \times H_{i,m} \right) + \sum_{K}^{\text{OPTION}} \left(CW_{m,k} + LK_{m,k} + SH_{m,k} + EDs \right) \right] \quad (3)$$

where EDs = other end use devices.

3.2. Prediction modeling

In prediction modeling of this study, secondary data have been used from Statistical Yearbook of Chongqing (2000–2012), Statistical yearbook of China (2000–2012) and China energy yearbook (2000–2012).

3.2.1. Grey model GM (1,1) and DGM (2,1) for prediction

Grey theory is an approach that can employ to build a forecast model to provide a better prediction and evaluation of data based on limited past samples or data. A first order differential equation is used in the GM (1,1) model to describe an unknown system. The object of the grey prediction GM (1,1) model is an uncertainty system. One new kind of grey model is the DGM (2,1) model that is developed by using the grey derivative and second-order grey derivative.

3.2.1.1. Main procedure of GM (1,1) model. The basic mathematical structure of grey model is given below.

Step 1: Assume $X^{(0)}$ as an original discrete time variable

$$X^{(0)} = \left\{ X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(i), \ldots, X^{(0)}(n) \right\} \quad (4)$$

where $X^{(0)}$ (i) is the time series data at time I and n must be equal to or larger than 4.

Step 2: A new sequence $X^{(1)}$ is developed based on the initial sequence $X^{(0)}$, through the accumulated generating operation (AGO)

$$X^{(1)} = \left\{ X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(i), \ldots, X^{(1)}(n) \right\} \quad (5)$$

where

$$X^{(1)}(k) = \sum_{i=1}^{K} X^{(0)}(i)\, k = 1, 2, 3, \ldots, n$$

Step 3: The first order differential equation of grey model GM (1,1) is then the following:

$$\frac{\mathrm{d}X^{(1)}}{\mathrm{d}t} + aX^{(1)} = b \quad (6)$$

According to the initial condition $X^{(1)}$ $(1) = X^{(0)}$ (1). The coefficients a and b can be acquired by using the least square method which is shown in the following equation

$$A = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B \right)^{-1} B^T Y_n \quad (7)$$

where

$$Y_n = \left[x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n) \right]^T$$

$$B = \begin{bmatrix} -X^{(1)}(2) & 1 \\ -X^{(1)}(3) & 1 \\ . & . \\ -X^{(1)}(n) & 1 \end{bmatrix}$$

and

$$X^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha) x^{(1)}(k-1), \quad k = 1, 2, 3, \ldots, n,$$

α is the weighting factor

Step 4: Obtain the forecast value

Once a and b are obtained (Eq. (6)), the grey differential equation can be used to forecast the value of state x at time instant $k+1$.

$$\hat{X}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] \times e^{-ak} + \frac{b}{a}, \quad k = 0, 1, 2, \ldots, n \quad (8)$$

Then the prediction or forecast value of the state x can be estimated by an inverse-accumulated generating operation (IAGO):

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (9)$$

Step 5: Mean relative percentage error (MRPE), which measures the percent of prediction accuracy can be found by the following equation:

$$\mathrm{MRPE} = \frac{1}{n}\sum_{k=1}^{n}\left[\frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)}\right] \tag{10}$$

3.2.1.2. The DGM (2,1) model. One type of single sequence second order linear dynamic model is the DGM (2,1) model which is fitted by differential equations.

Suppose an original series to be $X^{(0)}$,

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\right\} \tag{11}$$

The accumulated generating operation (AGO) generates a new sequence $X^{(1)}$.

$$X^{(1)} = \left\{X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(n)\right\} \tag{12}$$

where

$$X^{(1)}(k) = \sum_{j=1}^{K} X^{(0)}(j) \qquad k = 1, 2, 3, \ldots, n$$

and developed a second-order differential equation:

$$\frac{d^2X^{(1)}}{dt^2} + a\frac{dX^{(1)}}{dt} = u \tag{13}$$

where

$$\hat{a} = [a, u]^T = \left(B^TB\right)^{-1}B^TY \tag{14}$$

$$Y = \begin{bmatrix} (x^{(0)}(2) - x^{(0)}(1) \\ (x^{(0)}(3) - x^{(0)}(2) \\ . \\ . \\ (x^{(0)}(n) - x^{(0)}(n-1) \end{bmatrix} \tag{15}$$

$$B = \begin{bmatrix} -x^{(0)}(2) & 1 \\ -x^{(0)}(3) & 1 \\ . & . \\ -x^{(0)}(n) & 1 \end{bmatrix} \tag{16}$$

According to (13), we have

$$\hat{x}^{(1)}(k+1) = \left(\frac{u}{a^2} - \frac{x^{(0)}(1)}{a}\right)e^{-ak} + \frac{u}{a}(k+1) + \left(x^{(0)}(1) - \frac{u}{a}\right)\left(\frac{1+a}{a}\right) \tag{17}$$

The prediction values of original sequence or values can be acquired by using inverse AGO to $x^{(1)}$. Namely,

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)(k = 0, 1, 2, \ldots, n) \tag{18}$$

$$= \left(\frac{u}{a^2} - \frac{x^{(0)}(1)}{a}\right)\left(1 - e^{a}\right)e^{-ak} + \frac{u}{a} \tag{19}$$

3.2.2. Polynomial model

Polynomial models are useful tools for linear models and are very robust with respect to change of data and location. Polynomial evaluation (polyval) is an effective tool to forecast the future based on the evaluation of past and present data. In MATLAB, polynomial evaluation is generally expressed by polyval, where y = polyval (p,x); [y,delta] = polyval (p,x,s). Here, y is predicted value by a polynomial based on input argument p. Polyval estimates p based on each element of x. A general equation for polyval is: $y = p_1x^n + p_2x^{n-1} + \cdots + p_nx + p_{n+1}$, where, p is a vector and x can be vector or matrix and s generates error and estimates delta, which is generated by polyfit. The polyval equation predicts the future according to degree by extrapolating actual data. The coefficients c in the polynomial for a degree d which fits on the vector p can be obtained by solving a linear equation solving. In this study cubic and quadratic fitting have been used because as the degree is increased, extrapolated points become more erratic. All the computations required for this study have been carried out on MATLAB R2011b version by preparing appropriate MATLAB routines..

3.2.3. ANN model

In artificial neural networks a back-propagation (BP) network can be used with one to multiple neurons and R inputs. Each input in the BP network is weighted with a suitable weighting w. Input of the transfer sigmoid function f is sum of the bias b and the weighted inputs wp. To generate output a, neuron can use any of the differentiable transfer functions f such as sigmoid, purelin. The basic structure of the NARX network is shown in Fig. 1.

BP was established by simplifying the Widrow–Hoff learning rule to transfer functions and multiple layer networks. Input and target vectors or metrics are used to train the network to minimize the network performance function net to achieve a low error between the target output t and network output *a*.

The ANN model is very popular for forecasting future demand and its accuracy is very high. In this study non-linear Auto-Regressive (NAR) network has been used. To use this network, there are some steps that need to be followed such as processing the data, training the network to achieve acceptable error, testing the network, and validating of the data. About15 hidden neurons and 1 delay have been used in the ANN for electricity consumption prediction, and 20 hidden neurons and 1 delay have been used in the ANN network for prediction of the total building energy consumption of Chongqing urban residential areas. After training, the lowest error was found to be 9 epochs for energy and 6 epochs for electricity consumption prediction (for training the trainlm algorithm has been used).

4. Results and discussion

4.1. Residential building energy consumption simulation

Simulation of energy consumption is a vital part of energy policy and decision making. In this study the total annual energy consumption of urban residential buildings of Chongqing has been calculated based on the field survey in the urban residential areas of Chongqing. The summary of the breakdown information for the simulation of urban residential energy consumption is shown in Table 1.

By applying Eq. (3) and four groups of end-use devices intensities, the forecast consumption was found to be about 217.7×10^8 kW h/year in 2013.

$$\begin{aligned} E_{CR} &= \sum_{m}^{\text{OPTION}} \frac{P_m}{F_m} \times \left[\left(\sum_{j} S_{j,m} \times UEC_{j,m} + E_m \sum_{i}^{\text{OPTION}} L_{i,m} \times Ca_{i,m} \times H_{i,m}\right) + \sum_{K}^{\text{OPTION}} \left(CW_{m,k} + LK_{m,k} + SH_{m,k} + EDs\right)\right] \\ &= (1605.96 \times 104/3)[(1 \times 1166.15\ \text{kW h/household/year}) \\ &\quad + (1 \times 11.83/\text{household} \times 0.01930\ \text{kW} \times 6.5\ \text{h} \times 365\ \text{days}) + (1385 + 260 + 390 + 323.93)\ \text{kW h/year}] \\ &= 217.7 \times 108 \quad \text{kW h/yearor} \quad 267.42 \times 10^4 \text{SCE} \end{aligned}$$

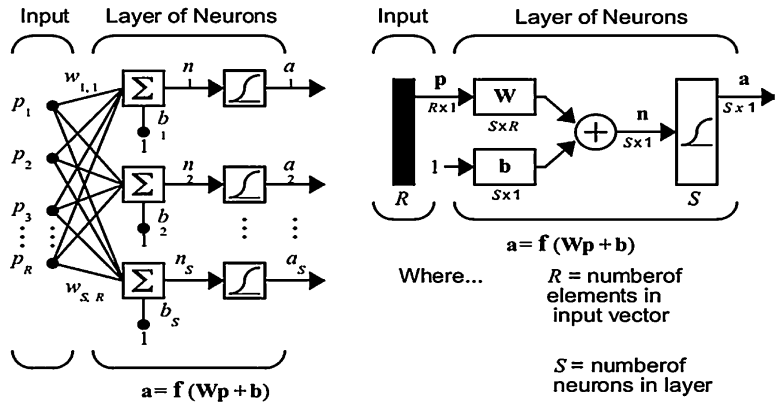

Fig. 1. Structure of NARX network.

The study hereby, simulates the total residential building energy consumption in urban areas by using macro and micro drivers. The simulation model calculates the consumption from downstream (e.g. household) level of a region and provides the actual scenario which can help to make the balance from upstream level (e.g. statistical level), and indirectly identify the energy loss (e.g. system loss, illegal consumption, etc.). Based on the simulation result, it was found the total energy consumption data (217.85×10^8 kWh or 267.41×10^4SCE) which is nearly equal with statistical data (291.75×10^4SCE) for the residential building at 2011. The result is slightly lower than the actual one, because the study assumed the round figure of per household population (e.g. 3). The result will be 289.79×10^4SCE which is very close to the actual statistical value, if the study considers the actual figure (e.g. 2.74).

4.2. Urban residential building energy consumption forecasting in Chongqing

The energy prediction can help to take decision of energy policy. It is important to select a valid and accurate model for prediction. Therefore, a comparative study on various prediction models is important to select the most effective one. The annual urban residential building energy consumption data (which includes lighting, HVAC, TV, refrigerator, domestic hot water, other end use devices and all types of fuel/energy e. g electricity, LPG, renewable energy, etc) from 2000 to 2011 of Chongqing was used to set up the two Grey prediction models [GM (1,1) and DGM (2,1)], a Polynomial model, a Polynomial regression model, a Regression analysis and an ANN model to compare the forecasting trends, growth rate and the accuracy of prediction among the studied models. The necessary data for making prediction have been collected from the statistical yearbook of Chongqing.

4.2.1. Energy consumption forecasting by GM (1,1)

The basic steps of constructing GM (1,1) model have been described below.

Step 1: By using Eq. (4), $X^{(0)}$ has been obtained, where $X^{(0)}$ as an original discrete time variable

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(i), \ldots, X^{(0)}(n)\right\}$$
$$= \left\{121.22, 123.08, \ldots, 291.75\right\}$$

Step 2: A new sequence $X^{(1)}$ is developed based on the initial sequence $X^{(0)}$, through the accumulated generating operation (AGO):

$$X^{(1)} = \left\{X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(i), \ldots, X^{(1)}(n)\right\}$$
$$= \left\{121.22, 244.3, \ldots, 2071.93\right\}$$

Step 3: The coefficients a and b can be acquired by using Eq. (7). $A = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y_n$

$$= [-0.0970, 86.6010]^T$$

Step 4: By using Eqs. (8) and (9), we can get the IAGO value. Then the prediction or forecast value of the state x can

Table 1
Summary of the breakdown data for energy consumption simulation.

Breakdown information	Value	Source
Locale, m	Urban	Study region
Total population in urban areas of Chongqing, P_m	1605.96×10^4	The Statistical Yearbook of Chongqing
Average number of people per household, F_m	3	
Electrification rate, E_m	100%	
Penetration of device or appliance j in percent appliance owned by household (values in excess of 100% would indicate more than one device per household on average), $S_{j,m}$	100%	Questionnaire Survey
Types of lighting bulb, i	Fluorescent, incandescent, CFL	
Number of lighting bulb of type i per household, $L_{i,m}$	11.83	
Power of bulb of type i, $Ca_{i,m}$	19.3 W	
Hours of use of bulb of type i, $H_{i,m}$	6.5 h/day	
Fuel type, k	LPG and electricity	
Lighting energy use of fuel k, $LK_{m,k}$	260 kW h/year	Zhou [23] and Hossain et al. [7]
Cooking and water heating energy use of fuel k per household per year, $CW_{m,k}$	1385 kW h/year	
Space heating and cooling energy use of fuel k, $SH_{m,k}$	390 kW h/year	
Other end use devices, EDs	323.93 kW h/year	

Table 2
Urban residential energy consumption forecasting in Chongqing (10^4SCE).

Year	Actual Value	Predicted value					
		GM (1,1) model	DGM (2,1) model	Regression analysis	Polynomial model	Polynomial Regression	ANN model
2000	121.22	121.22	125.47	121.22	121.51	92.62	121.22
2001	123.08	103.29	128.15	95.50	120.30	107.17	123.08
2002	124.12	113.81	131.63	111.78	122.25	121.72	124.90
2003	120.15	125.40	136.15	128.07	127.35	136.28	120.83
2004	121.78	138.18	142.00	144.35	135.60	150.83	121.78
2005	159.83	152.25	149.60	160.63	147.00	165.38	123.67
2006	176.98	167.76	159.45	176.91	161.55	179.94	209.69
2007	179.13	184.85	172.22	193.20	179.26	194.49	179.13
2008	188.46	203.67	188.79	209.48	200.11	209.04	188.46
2009	228.28	224.42	210.27	225.76	224.12	223.6	228.28
2010	237.15	247.28	238.13	242.05	251.29	238.15	237.15
2011	291.75	272.47	274.28	258.33	281.60	252.71	291.75
MRPE (%)		0.47	0. 85	0.44	0.65	0.91	0.09

be estimated by an inverse-accumulated generating operation (IAGO): $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$
$= (1014.013814 - 920.27)\,e^{-ak} = 93.74e^{-ak}$

This is the final equation for predicting the time series value of k.

By the same procedure, residential building electricity consumption has been estimated by GM (1,1).

4.2.2. Energy consumption forecasting by DGM (2,1)

The basic steps of constructing DGM (2,1) model have been described below.

Step 1: By using Eq. (11), original series $X^{(0)}$ has been adopted,

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\right\} \quad (11)$$
$$= \left\{121.22, 123.08, \ldots, 291.75\right\}$$

Step 2: By using Eqs. (13)–(16), the coefficients a and u can be acquired.

$$\hat{a} = [a, u]^T = \left(B^TB\right)^{-1}B^TY \quad (14)$$
$$= [-0.256, -29.9]^T$$

Step 3: By using Eqs. (17)–(19), AGO value can be obtained. Then the prediction values of original sequence or values can be acquired by using inverse AGO to $x^{(1)}$.

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)(K = 0, 1, 2, \ldots, n) \quad (18)$$

$$= \left(\frac{u}{a^2} - \frac{x^{(0)}(1)}{a}\right)(1 - e^a)\,e^{-ak} + \frac{u}{a} \quad (19)$$
$$= 7.15e^{-ak} + 116.8$$

This is the final equation for predicting the time series value of k.

Similarly, electricity consumption in residential building has also been forecasted. Rest of the models, such as ANN, Regression analysis, Polynomial and Polynomial regression model have been done by using MATLAB 2011a version software.

Urban residential building energy consumption in Chongqing is increasing year by year. The study has compared six prediction models, in which the Mean Relative Percent Error (MRPE) was found at 0.47%, 0.85%, 0.44%, 0.65%, 0.91% and 0.09% for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model, respectively. Lowest MRPE was for ANN (0.09%) and highest was for Polynomial regression model (0.91%). Among the forecasted models, the value found by ANN was more accurate and closest to the actual value. The comparisons of actual and forecasted values by multiple models from 2000 to 2011 are shown in Table 2. According to the prediction models, in 2025, the energy consumption will be 1059.27, 6129.05, 486.29, 1589.03, 576.05 and 1005 (10^4 SCE) for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model, whereas 300.22, 321.14, 274.61, 378.2, 313.97 and 335.98 (10^4 SCE), respectively, was in 2012. The residential building energy consumption predictions values were highest for DGM model and lowest for Regression analysis then the other 5 models.

Table 2 demonstrates that the ANN model has the smaller mean relative percentage error (MRPE) than the other models. This means that the accuracy rate of ANN model is higher than the other 5 models. Therefore, for short term prediction, urban residential building energy consumption will be at 1005 (10^4 SCE) in 2025 which is about three times higher than that of 2012. The comparison of forecasted values with actual values and the future prediction of the total urban residential building energy consumption in Chongqing from 2000 to 2025 by the multiple models are shown in Fig. 2. Due to higher error and un-compatible has found in DGM (2,1) model, this has been excluded from the figure. The figure shows that the ANN and GM (1,1) model have comparatively similar trends. However, the DGM (2,1) model is found to have a higher trend.

4.3. Urban residential building electricity consumption forecasting in Chongqing

Electricity is one type of energy, which is highly consumed by building occupants and the building services systems. Previous urban residential electricity consumption data (electrical devices which includes lighting, HVAC, TV and other electronic end use devices) from 2000–2011 were used to set up the GM (1,1) model, DGM (2,1) model, a Regression model, a Polynomial model, a Polynomial regression model and an ANN model to forecast present and future electricity consumption growth rate, and to compare forecasting trends and the accuracy of the models. The actual and forecasted values of building electricity consumption are shown in Table 3. The MRPE were 0.12%, 18.48%, 0.44%, 0.41%, 0.58% and 0.09% for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model. The ANN and GM (1,1) model have the smallest relative error of 0.09% and 0.12%, respectively. This shows that the accuracy rate is higher in the ANN and GM (1,1) model than in the other models. The Polynomial model, Polynomial regression model and Regression model have been found to have medium MRPE compared to ANN and GM (1,1) model, and the highest MRPE, about 18.48%, has been found in DGM (2,1) model. The comparison of forecasted values with actual values and future prediction of urban residential electricity consumption of Chongqing from 2000 to 2025 by multiple models are shown in Fig. 3. According to the models, electricity

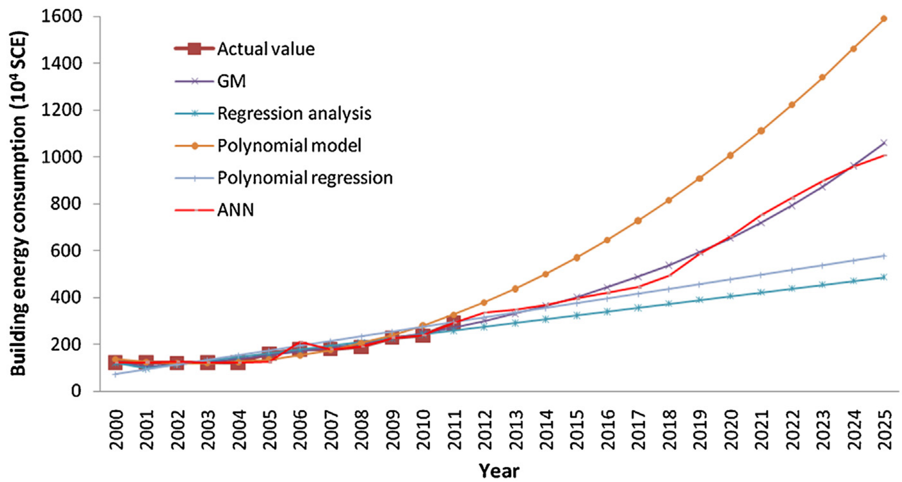

Fig. 2. Comparison of urban residential building energy consumption forecasting of Chongqing by multiple model.

Table 3
Urban residential electricity consumption forecasting in Chongqing (10^8 kW h).

Year	Actual value	Predicted value					
		GM (1,1) model	DGM (2,1) model	Regression analysis	Polynomial model	Polynomial regression	ANN model
2000	32.50	32.5	32.99	32.50	32.29	25.69	32.50
2001	34.23	29.67	34.12	27.32	32.8	29.8	34.02
2002	35.05	32.58	35.50	31.80	34.03	33.91	35.05
2003	31.82	35.79	37.18	36.28	35.97	38.01	31.82
2004	36.21	39.3	39.23	40.76	38.64	42.12	36.21
2005	41.50	43.16	41.75	45.24	42.03	46.23	41.50
2006	51.92	47.4	44.82	49.72	46.13	50.34	51.92
2007	51.21	52.06	48.57	54.20	50.96	54.44	51.21
2008	57.63	57.17	53.16	58.67	56.51	58.55	57.63
2009	62.83	62.79	58.77	63.15	62.78	62.66	62.83
2010	64.02	68.95	65.62	67.63	69.77	66.77	64.02
2011	80.47	75.73	74	72.11	77.48	70.87	80.47
MRPE(%)		0.12	18.48	0.44	0.41	0.58	0.09

consumption in residential building will be increased from 83.17, 50.77, 76.59, 85.9, 74.98 and 70.14 (10^8 kW h) in 2012 to 281.17, 466.35, 134.81, 261.02, 128.38 and 264.81 (10^8 kW h) for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model, respectively to 2025. The ANN and GM (1,1) models show the constant growth rate of total residential electricity consumption. This was found to be more accurate based on MRPE. The Regression model, Polynomial model and Polynomial regression model show medium accuracy based on the MRPE of the study, whilst DGM (2,1) shows the lowest accuracy (MRPE 18.48%).

Therefore, it can be concluded that ANN and GM (1,1) models can be used for forecasting electricity consumption with higher accuracy and could be employed for decision making on energy management and policy. Hence, for short term prediction,

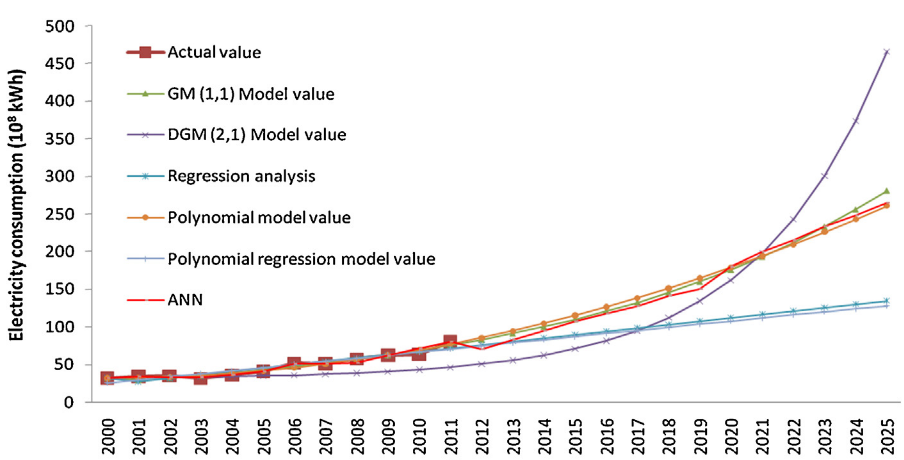

Fig. 3. Comparison of urban residential building electricity consumption forecasting of Chongqing by multiple model.

Table 4
Accuracy test of the models.

Category	Test		GM(1,1) model	DGM (2,1) model	Regression analysis	Polynomial model	Polynomial regression	ANN model
	MRPE (%)		0.47	0. 85	0.44	0.65	0.91	0.09
Total energy consumption	Regression Statistics	t Statistics	14.485	16.264	10.034	12.942	8.339	12.194
		P value	4.89E − 08	1.6E − 08	1.54E − 06	1.43E − 07	8.17E − 06	2.51E − 07
		R^2 value	0.955	0.964	0.910	0.944	0.874	0.937
	MRPE (%)		0.12	18.48	0.44	0.41	0.58	0.09
Total electricity consumption	Regression Statistics	t Statistics	14.468	13.754	10.845	15.814	9.342	18.432
		P value	4.95E − 08	8.02E − 08	7.52E − 07	2.1E − 08	2.96E − 06	4.76E − 09
		R^2 value	0.954	0.950	0.922	0.962	0.897	0.971

Table 5
Comparison of forecasting rate by different models.

Category	Increasing rate (%) compared with 2011 value						
	Year	GM (1,1) model	DGM (2,1) model	Regression analysis	Polynomial model	Polynomial regression	ANN model
Total energy consumption	2020	123.59	501.56	38.77	245	62.89	126.25
	2025	263.14	2000.79	72.26	444.65	97.45	244.47
Total electricity consumption	2020	118.72	102.03	39.70	122.77	34.01	124.22
	2025	249.41	479.53	67.53	224.37	44.43	229.24

electricity consumption of residential building will be at 264.81 (10^8 kW h) by ANN model in 2025 which is about four times higher than that of 2012.

4.4. Prediction precision

The mean relative percentage error (Eq. (10)) of the total urban residential building energy consumption and electricity consumption of Chongqing is shown in Table 4. The lower MRPE indicates higher accuracy of prediction. The lowest MRPE has been found in ANN model (0.09%) while the highest MRPE has been found in Polynomial regression model (0.91%) for energy consumption forecasting. According to the regression statistics test, P values were 4.89E − 08, 1.6E − 08, 1.54E − 06, 1.43E − 07, 8.17E − 06 and 2.51E − 07 at GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model. In addition, T statistics values were 14.45, 16.26, 10.03, 12.94, 8.34 and 12.19 for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model. According to R^2 value, P value, t statistics value, every model value is statistically significance. Therefore, in this study, the ANN model is the most acceptable model for residential building energy consumption.

Similarly, the lowest MRPE was found in the ANN model (0.09%) whilst the highest value has been found in the DGM (2,1) model (18.48%) for electricity consumption. Therefore, the ANN model is more acceptable for residential building electricity consumption forecasting in the studied region, and DGM (2,1) can be rejected for this case. In urban residential building electricity consumption analysis, the ANN model regression statistics are stronger than the other models' regression statistics. According to regression statistics, the R^2 value (the percentage of variation which is estimated by the regression statistics) for the GM model (95.44%), DGM model (94.98%), Regression model (92.16%), Polynomial model (96.16%) and Polynomial Regression model (89.72%) are lower than the ANN model (97.14%). For electricity consumption in residential building, P values were 4.95E − 08, 8.02E − 08, 7.52E − 07, 2.1E − 08, 2.96E − 06 and 4.76E − 09 at GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model. Every P value is lower than the critical value (α) 0.05. In addition, t statistics values are 14.47, 13.75, 10.85, 15.81, 9.34 and 18.43 for GM (1,1), DGM (2,1), Regression analysis, Polynomial, Polynomial regression and ANN model. According to R^2 value, P value, t statistics value, every model value is statistically significance. The regression statistics for the ANN model is stronger than the other forecast models' regression statistics and statistically significant with 95% level of significance.

GM (1,1) also performed with more accurate results, but difficulties have been found when the sample size is large. Where, ANN model has no difficulties with sample size. Therefore, it can be concluded from the study that the ANN model is the more acceptable model for prediction than the other models.

4.5. Comparison of forecasting rate

According to the "Prediction precision" described in Section 4.4, the ANN and the GM (1,1) model are more acceptable than the other models (from both statistical test and MRPE). Hence, using the GM (1,1) model the total residential building electricity consumption rate in urban areas of Chongqing is estimated to increase by 118.71% and 249.41% in 2020 and 2025, respectively, compared to the actual 2011. For ANN model, it will be increased at 124.22% and 229.241% in 2020 and 2025, respectively, compared to the actual 2011.

Similarly, the total residential building energy consumption rate of urban areas in Chongqing will increase by 123.59% and 263.14%, by GM (1,1), and 125.25% and 224.47% as forecast by ANN model in 2020 and 2025 based on the 2011 value. The increasing rate of different models is shown in Table 5.

5. Conclusions

The present study has explored the potential of six time series models in energy consumption forecasting for urban residential buildings in Chongqing. For short-term forecasting, the results clearly indicate that values forecasted by ANN model are very much close to the real values. Chongqing is considered as a development hub of south-west China, where energy consumption and demand are increasing rapidly with the development of all sectors of the economy, especially in residential sector. This study simulates the urban residential building energy consumption in Chongqing on the basis of various energy drivers and end-use appliances and applications. The study also forecasts and compares the residential building energy consumption during the period 2000-2025 by using GM (1,1), DGM (2,1), Regression model, Polynomial model, Polynomial regression model and ANN model. It is important to select a valid and accurate model for prediction, as well as for energy policy. The precision of the se models has been analyzed. The precision of the results shows that the accuracy of ANN model is higher than the other five models based on MRPE and other statistical results in both of the measured sectors. Therefore, based on the predicted results by ANN, the study found that the total residential energy consumption will be increased at 125.25% and 244.47% in 2020 and 2025, respectively, compared to 2011 value of urban areas in Chongqing, and total residential building electricity consumption in urban areas of Chongqing will increase at 124.22% and 229.24% in 2020 and 2025, respectively, compared to 2011. Residential building consumes a considerable portion of the total energy of a city or country. The total energy consumption of urban residential building in Chongqing is increasing rapidly. Hence, the study will be helpful in assessing the future energy demand and taking action for energy efficiency and policy making.

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