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Community load prediction: methodology and a case study

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Abstract

As an important part of green eco-community planning, reasonable community energy planning requires accurate community load prediction. Hence, this paper focuses on the method of community load prediction. Given that community energy planning has great uncertainty and forward-looking requirements, this paper proposes an integrated method of buildings load prediction, which combines building simulation and scenario analysis. We apply scenario analysis to avoid simply adding up the loads which leads to overestimation. Establishment and calibration of the prototypical models are carried out. Using the proposed method, a case study is conducted to predict the cooling and heating load of a CBD in Shanghai. The results show that the energy system operates at relatively low efficiency and adjustment of area ratio of different building types is suggested.

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Keywords: Community Load Prediction; Prototypical Models; Simulation; Scenario Analysis;

1. Introduction

China is now in the mid-to late fast-urbanization period. In 2015, the urbanization rate has reached 56.1% and the population of urban permanent residents was 0.77 billion. The predicted urbanization rate in 2030 is 70%. Under such condition, green eco-community was proposed and the government takes it as a significant solution to sustainable municipal development. With the proposal and implementation of a series of policy and under the support and encouragement of the government, the construction of green eco-community will prevail. At present, community

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energy planning in China consists of electricity planning, heating planning, gas planning etc. There is no coordination among these planning agencies. Thus, repetitive energy planning happens, which leads to a large amount of waste[1].

Effective community energy planning requires accurate prediction of community loads. Zhao and Magoules[2] reviewed the prediction methods on building energy consumption and proposed future prospects. Signor et al. [3] developed a regression model with seven variables to predict the electricity consumption in the offices in 14 Brazilian cities. Warnken et al. [4] focused on exploring the methods to report the sector-wise energy consumption in the Australian tourist accommodation industry. Nizami and Al-Garni [5] developed a two-layer feedforward neural network model to predict the electrical energy consumption; the model was validated using seven-year measured data. Olofsson and Andersson [6] predicted the annual energy consumption for heating and internal use in six single-family buildings using the ANN (artificial neural network) model. Gonzalez and Zamarreño [7] forecasted hourly energy consumption in buildings using the ANN model, with forecasted temperature, current load and corresponding hours of the day as inputs. Eiman Tamah Al-Shammari et al. [8] used SVMs with FFA to predict the loads in district heating systems. Shahaboddin Shamshirband [9] applied adaptive neuro-fuzzy inference system to predict the loads in district heating systems. Hassan Harb et al. [10] developed grey-box models and trained them with measured data to predict the thermal response of buildings. Francesco Ferracuti et al. [11] compared three data-driven models for short-term prediction in real buildings, and found that they show good accuracy at 15min, 1h and 3h prediction periods.

Zhengen Ren et al. [12, 13] built a database of prototypical models and energy consumption, and applied the calibrated models to predict the electricity consumption of end users in a residential sector. Yoshiyuki Shimoda et al. [14, 15] also built detailed residential models to predict energy savings of energy-efficient measurements and greenhouse emissions at the city scale. Nuria Garrido Soriano et al. [16] adopted the scenario analysis method to find out the energy saving potential, economic performance, and greenhouse gas emissions. A comparison of the community load prediction methods is presented in Table 1. It can be seen from the table that the area load index method always leads to overestimation, while the statistical prediction method requires huge amount of data. Presently, in China, one of the main reasons for the difficulty in load prediction is the lack of required data. In most cases, only monthly or annual energy consumption data are available.

Table 1 Comparison of community load prediction methods

Methods		Prediction stage			Prediction period			Features
		Energy usage planning	System design	System operation	short	medium	long	
Area load index method		√	√				√	Static method, not capable of reflecting load dynamic characteristics, overestimates loads.
Statistical model prediction method	Regression analysis			√	√	√	√	Requirement of large amount of data, poor prediction accuracy
	Time series			√	√			Requirement of large amount of data and mastery of theoretical knowledge, complex model building process
	Artificial neural network			√	√	√	√	Requirement of large amount of data, capable of dealing with nonlinear relationships, high prediction accuracy, difficult model, and parameter selection
	Support vector machine			√	√			Requirement of small amount of data, capable of dealing with nonlinear relationships, high prediction accuracy, complex model
	Grey box	√	√	√		√	√	Requirement of small amount of data, average prediction accuracy
Simulation prediction		√	√			√	√	Requirement of climate parameters and detailed building information, high prediction accuracy
Scenario analysis		√	√			√	√	Requirement of various scenarios, uncertainties still remain

This paper proposes an integrated method of community's load prediction, which combines building simulation and scenario analysis. The main research objectives are: 1) To propose a method of community load prediction; 2) To conduct a case study applying the proposed method to a CBD's load prediction.

2. Methodology

Owing to the absence of design parameters at the planning stage, an integrated method combining simulation and scenario analysis of load prediction is presented.

Prototypical models are required to predict building loads when no detailed information is available on the buildings at the planning stage. Prototypical models represent the buildings' form, scale, envelop, internal loads, and load pattern in the planning district [17]. They are crucial for load prediction, and directly influence the prediction accuracy and rationality. Modelling information is obtained mainly from three sources: planning information, pertinent design regulations, and on-site investigations.

The only statistical data available at present are on energy consumption, while load data are absent. Thus, with model calibration regarding energy consumption, the model's load output is considered to represent the real building's load profile. The building scale is enlarged from an individual building to a building block while performing community load prediction. Current methods mainly add up only the load of each building, while there are many other parameters that may influence the community load. A modified formula considering microclimate, simultaneity usage coefficient, etc. is given below.

$$Q'_t = \alpha_1 \cdot \alpha_2 \cdot \alpha_3 \cdot \sum_{j=1}^{n} q_{jt} S_j \quad (t=1,\ 2,\ 3\ldots,\ 8760) \tag{1}$$

Where:

$Q_t{}'$——community total hourly load, W;

q_{jt}——hourly load index per area of building type j, W/m^2;

Sj——total area of building type j, m^2;

n—— total number of building types;

α_1— —correction of microclimate;

α_2— — simultaneity usage coefficient;

α_3— —correction of other factors.

At the planning stage, the building parameters such as building form are not determined, and it is a complicated task to obtain the influence of microclimate by modelling. It is necessary to find a method to quantify the impact of microclimate, but this is not part of this study.

In practice, simultaneity usage coefficient is chosen most often based on investigations or design manuals, and it is difficult to determine its value. Merely adding up the hourly load of each building would lead to overestimation of the total load. Hence, after building up the prototypical models, scenario analysis is proposed to solve this problem. Different scenarios of internal load intensity, envelope thermal performance, and schedules can be set up. Considering the probability of occurrence of each scenario, adding up the hourly load of each scenario can yield the integrated hourly load; this solves the problem of determining a proper simultaneity usage coefficient. Owing to the large amount of influencing factors, complexity of the problem, lack of actual data, and limitation of the present studies, the correction factors in this study are assumed to be 1.

The steps involved in this combined method can be seen from Fig. 1. Firstly, representative energy consumption data from similar buildings in a similar district are collected to serve as input for the model calibration. The error between the measured data and simulated data is often used to evaluate the simulation results. When the error is within the stipulated range, the model is regarded as acceptable. The ranges of acceptable errors are listed in

Table 2. In this study, because of the lack of monthly energy usage data, annual consumption data are used for calibration. Thus, an annual error within ±10% is considered acceptable.

Table 2 Acceptable error ranges for model calibration （%）

	China's technical code[18]	IPMVP[19]	ASHRAE Guideline 14[20]	FEMP[21]
EER_{month}	±15	±20	±5	±15
EER_{year}	-	-	-	±10
$CV(RMSE_{month})$	10	5	15	10

EER_{month}: monthly error;
EER_{year}: annual error;
$RMSE_{month}$: monthly root mean squared error;
CV: coefficient of variation.

Prototypical models are built based on the parameters obtained from the investigations. In this study, the input parameters of prototypical models are determined according to the national and local building design regulations. Next, the models are calibrated using the energy consumption data until the variations are brought within the acceptable range. During calibration, simulation errors are considered acceptable by adjusting the climate parameters, internal loads, HVAC settings, air infiltration rate, non-HVAC system parameters, etc. Then, different scenarios and their probabilities are set. Finally, when the area of each building type is known, the community load can be calculated using Eq. (1).

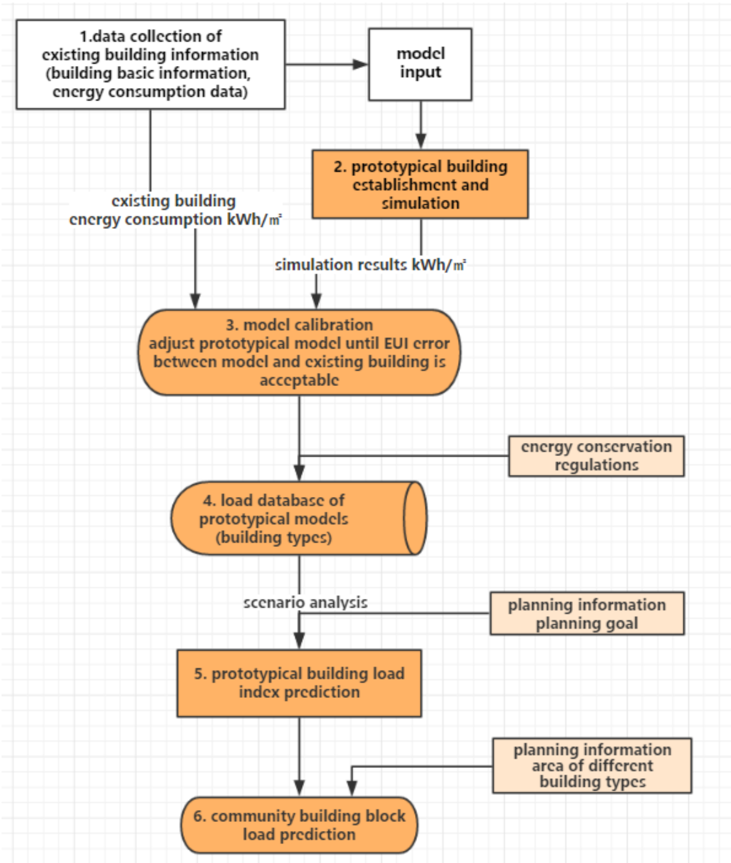


Fig. 1. Community building load prediction flowchart

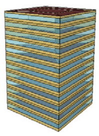
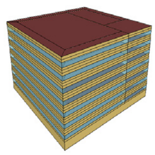
3. Results and discussion

3.1. Build and calibrate prototypical building models

The prototypical building model is the key to load prediction, and directly influences the prediction accuracy. The annual energy consumption data of buildings with similar functions in the same district must be collected; these data will be used for calibrating the model.

Prototypical models are not built based on real buildings, but are defined only for those groups of buildings that can reflect the load and energy consumption patterns in the specific district. In this study, prototypical models are built and calibrated based on the information from regulations and investigations, and simulation is conducted using EnergyPlus. Detailed input information is listed in Table 3.

Table 3 parameters of prototypical models

Type	Office	Shopping mall	Hotel
Area	27428.6 m2	29575 m2	23316 m2
Shape coefficient	0.1	0.7	0.25
Window-wall ratio	0.5	0.5	0.5
Floors	12	1 floor underground, 7 floors aboveground	12
Story height	4m	3.5m	Ground floor 5, others 3.5m
Shading	No	No	No
Orientation	south	south	south
Building model visualization			

After building up the models, calibration is an important step. By performing calibration, the models can be checked again, and their representativeness and reliability can be ensured. The preliminary input parameters are chosen mostly from the relevant design regulations, and may deviate from the real data; hence, calibration is necessary. Owing to lack of monthly energy consumption data, calibration can be done only based on the annual energy consumption and annual sub-metering data. During calibration, the variations are brought within the acceptable range by adjusting the climate parameters, internal loads, HVAC settings, air infiltration rate, non-HVAC system parameters, etc. The measured data are taken from Ref [22]. It is assumed that the simulation results acceptable when the deviation is within $\pm 10\%$ from the median value of the measured data [20].

The calibrated models can represent only the load and energy consumption of current buildings, but when used for load prediction, appropriate design requirements must be taken into consideration. Thus, scenario analysis was adopted together with the design goal and investigations on similar buildings to adjust the influencing factors such as envelope thermal performance, internal loads, and operation parameters, and predict the building loads under the integrated scenarios. According to Shanghai Design Standard for Energy Efficiency of Public Buildings [23] and Design Code for Heating Ventilation and Air Conditioning of Civil Buildings [24], the scenarios of occupant density, lighting intensity, and equipment intensity are determined with three scenarios for each internal load. The scenario settings are presented in Table 4Table 4:

Table 4 Scenario settings of internal loads

Building type	Scenario type	Occupancy density (m^2/person)	Lighting intensity (W/ m^2)	Equipment intensity (W/ m^2)
Office	1	4	11	20
	2	8	18	13
	3	10	9	15
Shopping mall	1	3	12	13
	2	4	19	13

	3	8	10	13
Hotel	1	15	15	20
	2	30	15	13
	3	25	7	15

3.2. Case Study

In this section, the prediction tool is run for predicting Hongqiao CBD's cooling, heating, and electricity loads.

There are three energy stations planned to meet the load requirement of the CBD. The total building area is 3.12 million m2. The supply area and building type of each energy station are listed in Table 5:

Table 5 Building type and supply area of energy stations

Energy station	Project progress	Offices (m^2)	Shopping mall(m^2)	Hotel (m^2)	Total (m^2)
1#	Stage 1	142 264.93	113 68.3	981 05.57	251 738.8
	Stage 2	172 797.34	127 451.32	—	300 248.66
	Stage 3	164 325	246 488	—	410 813
	Sum	479 387.27	385 307.62	981 05.57	962 800.46
2#		435 667	401 271	——	836 938
3#		751 930	579 215	——	1 331 145

The main building types planned in this project are commercial offices, commercial services, hotels, and apartment hotels. Thus, prototypical models of offices, shopping malls, and hotels are applied in the study.

Based on the functional orientation and experience of the CBD, the probabilities of occurrence of the three scenarios for all the building types are determined; these are listed in Table 6. For each building type, the total probability of occurrence of the three scenarios sums up to 1. For instance, for office buildings, the probabilities for scenarios 1, 2, and 3 are 0.3, 0.4, and 0.3, respectively, which add up to 1. Then, the integrated load index can be calculated by combining the values for the scenarios.

Table 6 CBD's scenario settings

Building type		Office	Shopping mall	Hotel
Weight	Scenario 1	0.3	0.3	0.3
	Scenario 2	0.4	0.4	0.5
	Scenario 3	0.3	0.3	0.2

After calculating the integrated load index, it is multiplied by the area to obtain the hourly community load. The cooling season in Shanghai is between May 16th and Oct. 15th, totaling 150 days, and the heating season is from Dec. 1st to Mar. 15th, totaling 105 days. When the load of each individual building is added, the correction factor will be 1. The calculated data are presented in Table 7Table 7.As can be seen from the table, different building types and areas have different values of peak load and peak-load time. Thus, by combining various building types and adjusting their building area ratios, the community peak load can be shifted.

Table 7 Load index and peak load time of each building type and energy station

type	Cooling load		Heating load	
	Peak load W/m^2	Time	Peak load W/m^2	time
Office	77.39	Aug. 7th 14:00	54.85	Jan. 2nd 8:00
Shopping mall	105.93	Jul. 19th 12:00	33.8	Dec. 29th 9:00
Hotel	72.77	Jun. 29th 18:00	47.62	Dec. 20th 7:00
1# 1st stage	70.7	Jun. 29th 17:00	43.41	Jan. 2nd 8:00
1# 2nd stage	88.04	Aug. 7th 14:00	34.54	Jan. 2nd 8:00
1# 3rd stage	92.44	Aug. 7th 14:00	32.31	Jan. 9th 9:00
2#	90.5	Aug. 7th 14:00	33.28	Jan. 9th 9:00
3#	88.31	Aug. 7th 14:00	34.03	Jan. 2nd 8:00

Part load ratio is used to analyze the annual hourly load and is calculated as follows:

$$\text{Part load ratio} = \frac{hourly\ load}{peak\ load} \quad (2)$$

According to the load prediction results, part load ratio and operation time of each energy station are listed below in Table 8:

Table 8 Cooling and heating part load ratio frequency

Energy station		Part load ratio			
		0%~25%	25%~50%	50%~75%	75%~100%
Cooling load	1#1st stage	68%	19%	10%	3%
	1#2nd stage	35%	40%	17%	8%
	1#3rd stage	24%	41%	26%	8%
	2#	32%	42%	18%	8%
	3#	34%	41%	17%	8%
Heating load	1#1st stage	63%	28%	8%	2%
	1#2nd stage	69%	21%	9%	1%
	1#3rd stage	71%	22%	6%	2%
	2#	68%	21%	9%	2%
	3#	68%	21%	9%	2%

According to the part load ratio results, for over 80% of the operating time in the cooling season and for over 90% of the operating time in the heating season, the part load ratio is under 50%. Thus, all the energy stations operate at a low part load ratio, which contributes to huge energy wastage. Besides, the load profile has great impact on the energy system configuration and operation. The more time the system operates at low part time ratios, the longer the payback period is. At the supply side, multiple energy sources can be used to keep the system at high efficiency. At the demand side, the area ratio of different building types can be adjusted to level the loads profile and reduce the peak-valley difference. Thus, load leveling performance plays a significant role in energy system configuration and operation.

4. Conclusion and future work

Given that community energy planning has great uncertainty and forward-looking requirements, an integrated method of buildings load prediction is proposed, which combines building simulation and scenario analysis. Prototypical models of office, commercial and hotel buildings in Shanghai are built and calibrated. Using the proposed method and scenario analysis, we predict cooling, heating and electricity loads of a CBD in Shanghai. The prediction results show that the energy stations at most time run at low part load ratio which causes energy waste. Thus, the area ratio of different building types may be adjusted to achieve a better load levelling performance.

Despite the merits of this study, problems still exist to be further tackled. Firstly, due to the lack of real investigated data, the data mining method doesn't play an effective role in load prediction. With the data accumulation on energy consumption platform of China's public building, this problem can be solved in the future. Secondly, regional micro-climate brings about uncertainties to community's building load, whereas at the planning stage parameters like building form are not determined. Thus, its effects on building load can hardly be studied by modeling. How to quantify the impacts of micro-climate remains unsolved.

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