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Community load leveling for energy configuration optimization: Methodology and a case study

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ABSTRACT

Load patterns have a significant effect on the configuration of an energy system. With a smoother load profile, the initial investment cost and operation and maintenance costs can be reduced. Adjustments in the area ratio of different types of buildings during early planning stage can be useful in leveling the loads. However, there are few studies till date on the guidelines for making such adjustments. This paper proposes a method to evaluate the performance of load leveling. Before evaluation, the load profile is obtained using a method that combines simulation and scenario analysis. Optimization of energy configuration for a typical case is conducted before and after load leveling adjustment to demonstrate the benefits of load leveling.

1. Introduction

Load pattern have a significant influence on the configuration of an energy system. Besides, the stability of heating and cooling loads is important for the smooth operation of the energy system. In fact, the more time the system operates at low part load ratios, the longer the investment cycle is, and the poorer the economic performance is (Lihui & Xiping, 2007). The difference between the peak and the valley can be reduced by introducing different forms of energy on the supply side. On the demand side, in the early stage of community planning the loads pattern of the district buildings can be leveled by adjusting the area ratio of the building types to have a smaller system capacity, lower operation cost, and longer life cycle of the equipment. Load leveling refers to the smoothing of the load profile by reducing the difference between the on-peak and off-peak loads (Hemmati & Saboori, 2016). However, few researchers have studied the adjustment principle, and the determination of the area ratio of the buildings is very subjective. Thus, this paper presents a method to evaluate the load levelling performance in a community.

At present, community 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 (Dengyun & Wenfa, 2011). Effective community energy planning requires accurate prediction of community loads. Zhao and Magoulès (2012) reviewed the prediction methods on building energy consumption and proposed future prospects. Signor, Westphal, and Lamberts (2001) developed a regression model with seven variables to predict the electricity consumption in the offices in 14 Brazilian cities. Warnken, Bradley, and Guilding (2004) focused on exploring the methods to report the sector-wise energy consumption in the Australian tourist accommodation industry. Javeed Nizami and ZAl-Garni (1995) 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 Anderson (2001) predicted the annual energy consumption for heating and internal use in six single-family buildings using the ANN (artificial neural network) model. González and Zamarreño (2005) forecasted hourly energy consumption in buildings using the ANN model, with forecasted temperature, current load and corresponding hours of the day as inputs. Al-Shammari et al. (2016) used SVMs with FFA to predict the loads in district heating systems. Shamshirband et al. (2015) applied adaptive neuro-fuzzy inference system to predict the loads in district heating systems. Harb, Boyanov, Hernandez, Streblow, and Müller (2016) developed grey-box models and trained them with measured data to predict the thermal response of buildings. Ferracuti et al. (2017) compared three data-driven models for short-term prediction in real buildings, and found that they show good accuracy at 15 min, 1 h and 3 h prediction periods.

Abbreviations: ANN, artificial neural network; SVM, support vector machine; FFA, firefly algorithm; MILP, mixed integer linear programming; CHP, combined heat and power; CCHP, combined cooling heating and power; CBD, central business district; SD, standard deviation; $EER_{monthly}$, monthly error; EER_{year}, annual error; $RMSE_{month}$, monthly root mean squared error; CV, coefficient of variation

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Nomenclature

a_i	Building area ratio of a certain building type

Ren, Paevere, and Mcnamara (2012) and Ren, Paevere, Grozev, Egan, and Anticev (2013) 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. Shimoda, Asahi, Taniguchi, and Mizuno (2007) and Shimoda, Yamaguchi, Okamura, Taniguchi, and Yamaguchi (2010) also built detailed residential models to predict energy savings of energy-efficient measurements and greenhouse emissions at the city scale. Garrido-Soriano, Rosas-Casals, Ivancic, and Castillo (2012) 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.

An effective energy system configuration can help avoid energy wastage and improve energy efficiency significantly. Sameti and Haghighat (2017) reviewed current mathematical approaches and studies at the district level and discussed the present constraints. Seo, Sung, Oh, Oh, and Kwak (2008) analyzed the economic performance of a cogeneration system by building an individual mathematical model of each residential building. Lozano, Ramos, Carvalho, and Serra (2009) employed MILP (mixed integer linear programming) to optimize the annual cost of a tri-generation system. Tveit, Savola, Gebremedhin, and Fogelholm (2009) built multi-cycle mixed integer nonlinear models to conduct economic optimization in a CHP system. Vesterlund, Toffolo, and Dahl (2017) applied a hybrid evolutionary-MILP optimization algorithm to meet the objective of achieving minimal total operating cost of a multi-source district heating system. MILP was also adopted in some other studies (Fazlollahi & Maréchal, 2011; Mehleri, Sarimveis, Markatos, & Papageorgiou, 2012; Omu, Choudhary, & Boies, 2013) for optimization purpose. Li, Mu, Li, and Li (2016) developed MILP models of a distributed energy resource system to achieve optimal design and operation and minimal CO_2 emission. In Cocchi, Andreini, Cassitto, Anatone, and Panone (2015), the optimization goal was to achieve the lowest cost or CO_2 emission of a CCHP plant. In Stoppato, Benato, Destro, and Mirandola (2016), energy and thermal storage equipment were taken into consideration while conducting optimization.

This paper proposes a quantitative index to assess load leveling performance; a method to evaluate the levelling performance is also proposed. Before conducting the evaluation, the community load is predicted using a bottom-up approach that combines simulation with scenario analysis. Besides, energy optimization is conducted using MILP to demonstrate the benefits of load leveling in a typical case in Shanghai.

The main objectives of this research are as follows.

1) To propose a method for community load prediction
2) To develop a quick calculation tool for community load prediction
3) To propose a method to evaluate load leveling performance
4) To conduct optimization of energy configuration of a typical case before and after load leveling adjustment

2. Methodology

2.1. Load prediction

Owing to the absence of design parameters at the planning stage, an

Table 1
Comparison of community load prediction methods.

Methods		Prediction stage			Prediction period			Features	Reference
		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.	
	Regression analysis			√	√	√	√	Requirement of large amount of data, poor prediction accuracy	Zhao and Magoulès (2012) , Signor et al. (2001), Warnken et al. (2004) and Ferracuti et al. (2017)
	Time series			√	√			Requirement of large amount of data and mastery of theoretical knowledge, complex model building process	
Statistical model prediction method	Artificial neural network			√	√	√	√	Requirement of large amount of data, capable of dealing with nonlinear relationships, high prediction accuracy, difficult model, and parameter selection	Zhao and Magoulès (2012), Javeed Nizami and ZAl-Garni (1995), Olofsson and Anderson (2001), González and Zamarreño, (2005) and Shamshirband et al. (2015)
	Support vector machine			√	√			Requirement of small amount of data, capable of dealing with nonlinear relationships, high prediction accuracy, complex model	Zhao and Magoulès, (2012) and Al-Shammari et al. (2016)
	Grey box	√	√	√		√	√	Requirement of small amount of data, average prediction accuracy	Zhao and Magoulès, (2012), Harb et al. (2016) and Ferracuti et al. (2017)
Simulation prediction		√	√			√	√	Requirement of climate parameters and detailed building information, high prediction accuracy	Zhao and Magoulès (2012), Ren et al. (2012), Ren et al. (2013), Shimoda et al. (2007) and Shimoda et al. (2010)
Scenario analysis		√	√			√	√	Requirement of various scenarios, uncertainties still remain	Garrido-Soriano et al. (2012)

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 (Han, Lin, Shu, & Xiang-Li, 2012). They are crucial for load prediction, and directly influence the prediction accuracy and rationality. Modeling 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 is the community total hourly load, W;

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

Sj is thetotal area of building type j, m^2;

n is the total number of building types;

α_1 is the correction for microclimate;

α_2 is the simultaneity usage coefficient;

α_3 is the correction for 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 modeling. 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

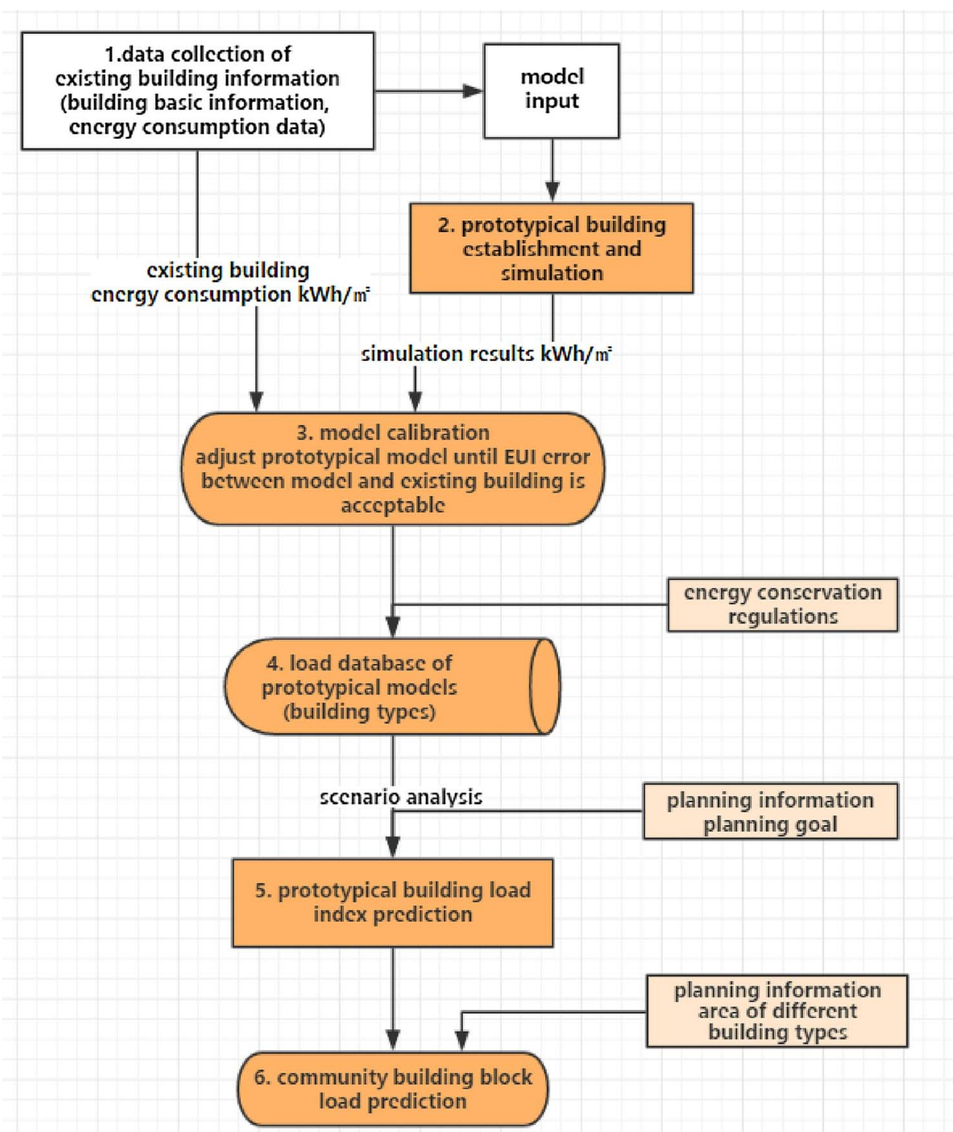


Fig. 1. Flowchart for community building load prediction.

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.

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).

2.2. Load leveling

Till date, there is no specific definition of load leveling, and there are no references on the method of adjusting the area ratio of different building types. Thus, in this study, a definition of load leveling is created, and suggestions are given for the area ratios of different building types. The CBD (central business district, comprising offices, shopping malls, and hotels) in Hongqiao, Shanghai is taken as an example to study the load performance before and after leveling.

2.2.1. Definition

To evaluate the characteristics of the loads, it is firstly necessary to obtain the load profile. By summing up the products of hourly load index (W/m^2) and the area ratio of each prototypical model under each scenario, the community's hourly load profile (W/m^2) is obtained.

The load rate and peak-valley difference ratio are defined by Eqs. (2) and (3), respectively. These terms are often used to present the peak-valley characteristics and stability of the load profile (Nan, 2012).

$$\text{Load rate} = \frac{\textit{average load}}{\textit{peak load}} \tag{2}$$

$$\text{Peak} - \text{valley difference ratio} = \frac{\textit{peak load} - \textit{valley load}}{\textit{peak load}} \tag{3}$$

The larger the load rate is, the higher the equipment utilization ratio is. The smaller the peak-valley difference ratio is, the less the fluctuation of the profile is, and the more stable the load is.

However, there are shortcomings in merely applying the load rate and the peak-valley difference ratio. Firstly, the use of the peak-valley difference ratio is limited, because when two curves have the same peak and same valley, this ratio remains the same irrespective of the load pattern. As for load rate, it can be seen from Fig. 2 that curve A and curve B have the same load rate (and peak-valley difference ratio), though curve A is more stable than curve B. Thus, these two indicators have their limitations, and it is necessary to have a more comprehensive evaluation parameter.

In statistics, both variance and standard deviation are used to measure the degree of fluctuation of data. Standard deviation has the same unit as the variable, and is therefore easier to understand than variance. Thus, standard deviation is more frequently applied (Probability and statistics, 2011).

The standard deviation (SD) is calculated as follows.

$$S = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \overline{x})^2}{N}} \tag{4}$$

The aim of load leveling is to achieve a stable and balanced load profile and to avoid frequent shifts between peaks and valleys. This study employs SD to describe the load profile. The smaller the SD is, the more stable the load profile is.

The standard deviations of the curve A is smaller than that of curve B; this is consistent with the previously mentioned conclusion that curve A is more stable. The authors assume that it is better to apply SD to indicate the degree of load fluctuation. Further, by combining both load rate and peak-valley difference ratio, a more comprehensive evaluation of the load profile can be performed.

Each community has its own load profile. During the planning stage, the building area ratio can be adjusted based on the predicted load profile to achieve better performance in terms of load leveling and peak shifting.

2.2.2. Load levelling method

This study covers mainly the load leveling performance of a community that includes offices, shopping malls, and hotels with different building area ratios. The schematic of the load leveling method is shown in Fig. 3. Firstly, the community's hourly loads can be calculated using the method mentioned above. Then, the standard deviation of each type of load, i.e., heating, cooling, and electricity is obtained. These deviations are the data sets of fuzzy clustering. Next, according to the outcome of fuzzy clustering, the building area ratios are classified into three groups: good, fair, and poor. By considering the leveling results of heating, cooling, and electricity loads, suggestions on building area ratio are given.

2.2.3. Fuzzy clustering

In this study, different building area ratios are to be categorized into three groups according to their standard deviation of each load type. The boundary of each group is not quite clear; and fuzzy clustering is applied to tackle with this. SPSS is used to conduct fuzzy clustering analysis of load data (Jing, Shiqun, Chao, & Erbao, 2012; Xinbo, 1999).

The fuzzy clustering method partitions the collection of n elements $U = \{u_1, u_2, \ldots, u_n\}$ into a collection of several fuzzy clusters with respect to some given criteria. Each element consists of m data $u_i = \{x_{i1}, x_{i2}, \ldots, x_{im}\}$ $(i = 1, 2, \ldots, n)$. The results of standard deviation are clustered into three groups: good, fair, and poor.

The original data matrix of the n elements to be clustered is

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

The building area ratios are clustered with the corresponding standard deviations being the elements' data u_i. Then, the original data set is processed with the following steps: normalization, building

Table 2
Acceptable error ranges for model calibration (%).

	China's technical code (Code, 2009)	IPMVP (PMVP, 2002)	ASHRAE Guideline 14 (ASHRAE, 2002)	FEMP (DOE FEMP, 2000)
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.

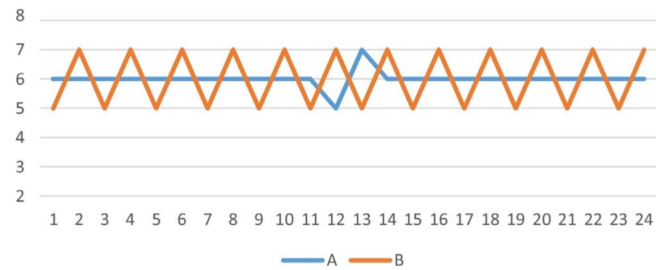


Fig. 2. Two curves with the same load rate and peak-valley difference ratio.

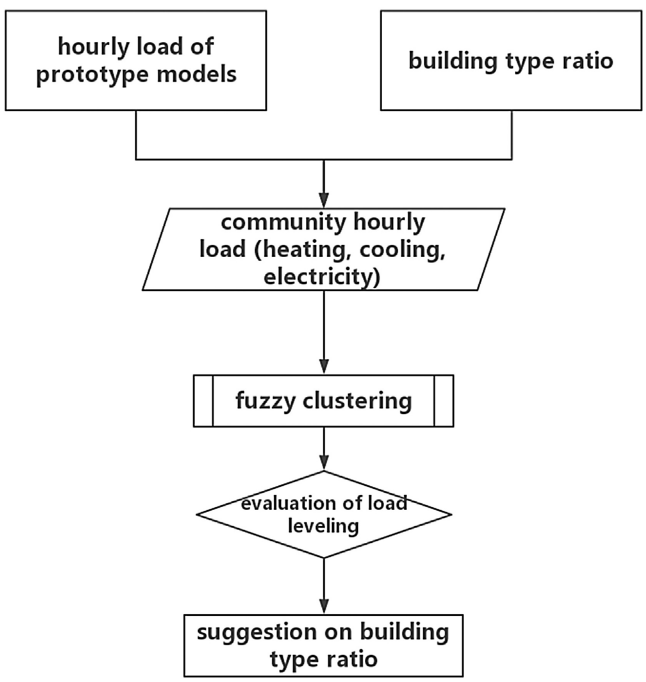


Fig. 3. Schematic of load leveling.

similar matrix, and clustering (Xinbo, 1999).

To avoid the influence of data dimensions, the data have to be normalized. The method of normalizing is shown below.

$$\text{Range:}\quad R_j = \max_{1\le i\le n} x_{ij} - \max_{1\le i\le n} x_{ij} \tag{5}$$

$$x_{ij}^{*} = \begin{cases} \dfrac{x_{ij} - \min\limits_{1\le i\le n} x_{ij}}{R_j} & \text{if } \mathrm{R_j} \neq 0 \begin{pmatrix} i = 1,\, 2,\, \dots n \\ i = 1,\, 2,\, \dots m \end{pmatrix} \\ 0.5 & \text{if } \mathrm{R_j} = 0 \end{cases} \tag{6}$$

Euclidean distance is applied to build the similar matrix $r_{ij} = (u_i, u_j)$ (i, j = 1, 2, …, n).

The Euclidean distance is calculated as follows.

$$d(x, y) = \sqrt{\sum_i (x_i - y_i)^2} \tag{7}$$

Then, the similar matrix is processed by clustering the two closest samples into the same category.

2.3. Optimization of energy system configuration

In this part of the paper, we mainly focus on the optimization results of energy configuration before and after load leveling. In this study, the district energy system provides chilled water, heating water, electricity to its serving district.

The problem of optimization of the community energy configuration can be expressed as follows. In the planning stage, optimal distribution of energy resources and a combination of energy conversion techniques are used to achieve the optimal objective. The optimal objective may be the minimum energy consumption or minimum cost, while ensuring that the CO_2 emissions meet the requirement.

At present, studies on community energy system mainly focus on three aspects: economy, energy efficiency, and environmental protection, among which economy is used most often. In this study, the minimum cost is taken as the goal of optimization.

The objective function is expressed as follows.

$$MinC^{TOT} = C^{INV} + C^{OM} + C^{FUEL} + C^{ElEC} + C^{Carbon} \tag{8}$$

where

C^{TOT} is the total cost;
C^{INV} is the cost of initial investment of equipment;
C^{OM} is the operation and maintenance fee;
C^{FUEL} is the fuel fee;
C^{ELEC} is the electricity fee;
C^{Carbon} is the carbon emission tax.

In this study, the energy systems for cooling, heating, and electricity are configured, and the influence of building area ratio on the energy system configuration is also studied. The DER-CAM (Distributed energy resources customer adoption model) is used to perform optimization of the configuration.

LBNL has been developing the DER-CAM since 2000. The optimal objective of the model is the minimum annual energy cost (electricity cost, fuel cost, distributed energy system cost, and operation and maintenance cost) keeping the CO_2 emission to the minimum level. DER-CAM can conduct optimization of single or multiple objectives and determine the optimal capacity combination and the corresponding operation strategy. DER-CAM applies MILP and the general algebraic modeling system (GAMS) solver, whose energy flow diagram is shown in Fig. 4.

The load models of DER-CAM include pure electricity load model, cooling load model, heating load model, pure natural gas load model, hot water load, etc. Besides, DER-CAM makes use of technologies such as photo-thermal, photovoltaic, conventional/neo-type generator, combined heat and power (CHP), thermal/electric storage, heat pump, and absorption chiller (Stadler, Groissböck, Cardoso, & Marnay, 2014). The input parameters are load data, energy price, etc. DER-CAM can provide outputs in terms of the optimal capacity configuration, optimized power generation, storage and operation method, electricity/fuel cost, maintenance and operation cost, energy consumption, and CO_2 emission. A schematic of DER-CAM's inputs and outputs is shown in Fig. 5.

3. Results and discussion

3.1. Load prediction

3.1.1. Building and calibrating 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. The detailed input information is listed in Table 3 and 4.

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

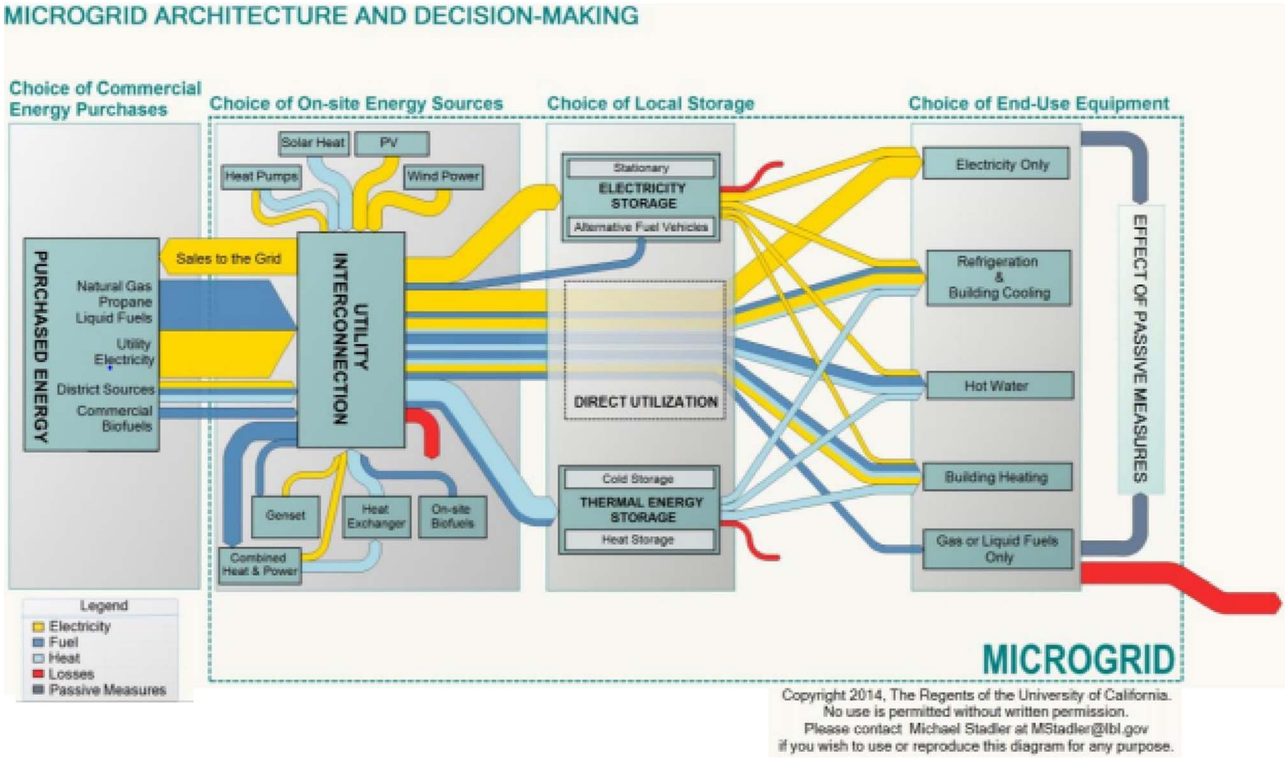


Fig. 4. DER-CAM energy flow diagram (Ghatikar, Mashayekh, Stadler, Yin, & Liu, 2016).

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. Annual Report on China Building Energy Efficiency (2009). It is assumed that the simulation results acceptable when the deviation is within ± 10% from the median value of the measured data (ASHRAE, 2002).

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

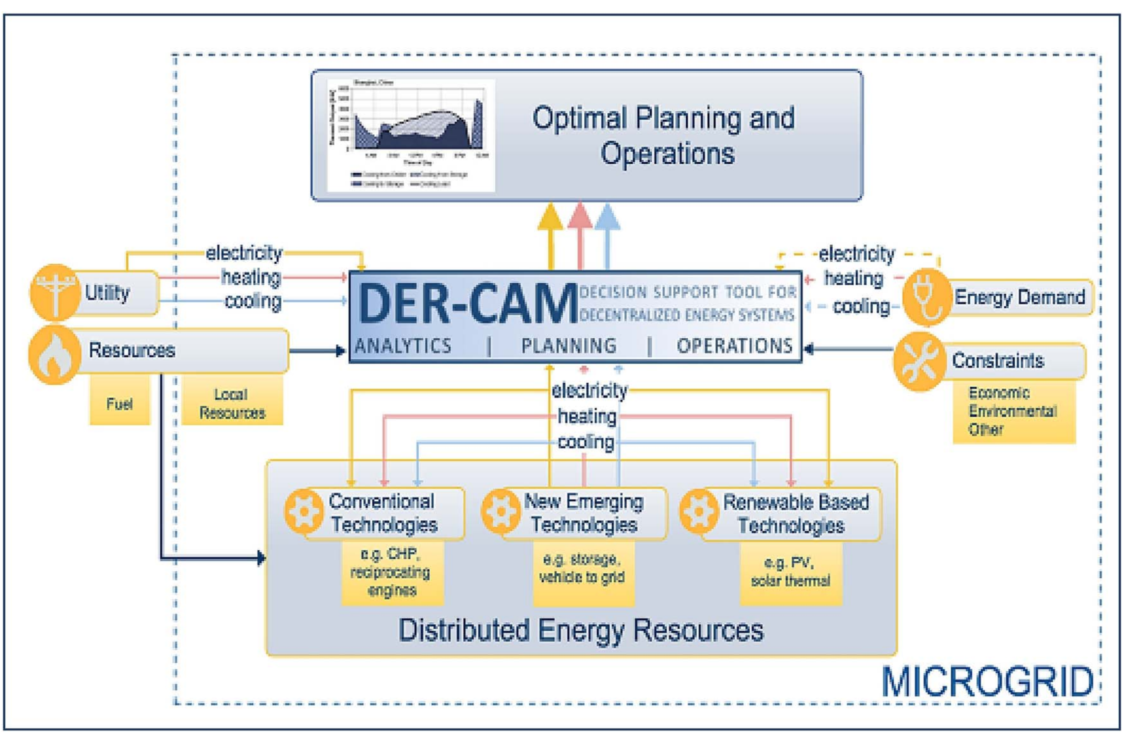


Fig. 5. DER-CAM's input and output schematic (Anonymous, 2017).

Table 3
Information for prototypical models.

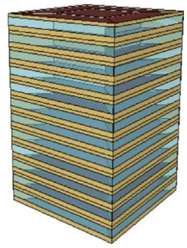
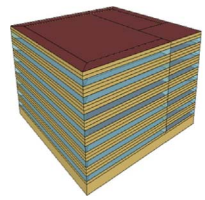
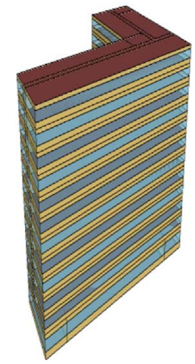
Type	Office	Shopping mall	Hotel
Area	27428.6 m^2	29575 m^2	23316 m^2
Shape coefficient	0.1	0.7	0.25
Window-wall ratio	0.5	0.5	0.5
Floors	12	1 floor underground, 7 floors aboveground	12
Story height	4m	3.5m	Ground: floor 5, others: 3.5 m
Shading	No	No	No
Orientation	south	south	south
Building model visualization			

Table 4
Envelop parameters of prototypical models.

Envelop	U-value (W/(m^2 K)	
Roof	0.5	
Exterior wall	0.8	
Exterior window	U-value	2.5
	Shading coefficient (SC)	0.35
	Solar heat gain coefficient (SHGC)	0.31

parameters, and predict the building loads under the integrated scenarios.

3.1.2. Tools for community load prediction

According to Shanghai Design Standard for Energy Efficiency of Public Buildings (Code, 2012) and Design Code for Heating Ventilation and Air Conditioning of Civil Buildings (Code, 2015), 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 5.

After determining the settings for each scenario and the corresponding probability, an integrated load index (W/m^2) can be calculated. Then, knowing the area of each building type, the community's hourly load can be obtained. With this method of building an off-line load database, a simple community load prediction tool was designed using EXCEL VAB to calculate the hourly cooling, heating, and electricity loads. Fig. 6 shows the framework of the calculation tool.

In this tool, a load database of different prototypes under different scenarios is built. For a specific building type, users can assign the probability of occurrence of each scenario, and the integrated load index will be calculated when the program is run. After entering the value of the building area of each building type in the program, the community's hourly load is obtained.

Furthermore, more building types and more scenarios can be added to obtain a more comprehensive database. Therefore, with this off-line database, there's no need to rebuild the models for prediction of community loads. Only the probability of occurrence of each scenario and area of each building type need to be entered. Then, the predicted values of the community's hourly loads can be calculated.

3.1.3. 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 m^2. The supply area and building type of each energy station are listed in Table 6.

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 7. 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.

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 8.

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.

Part load ratio is used to analyze the annual hourly load; it is

Table 5
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

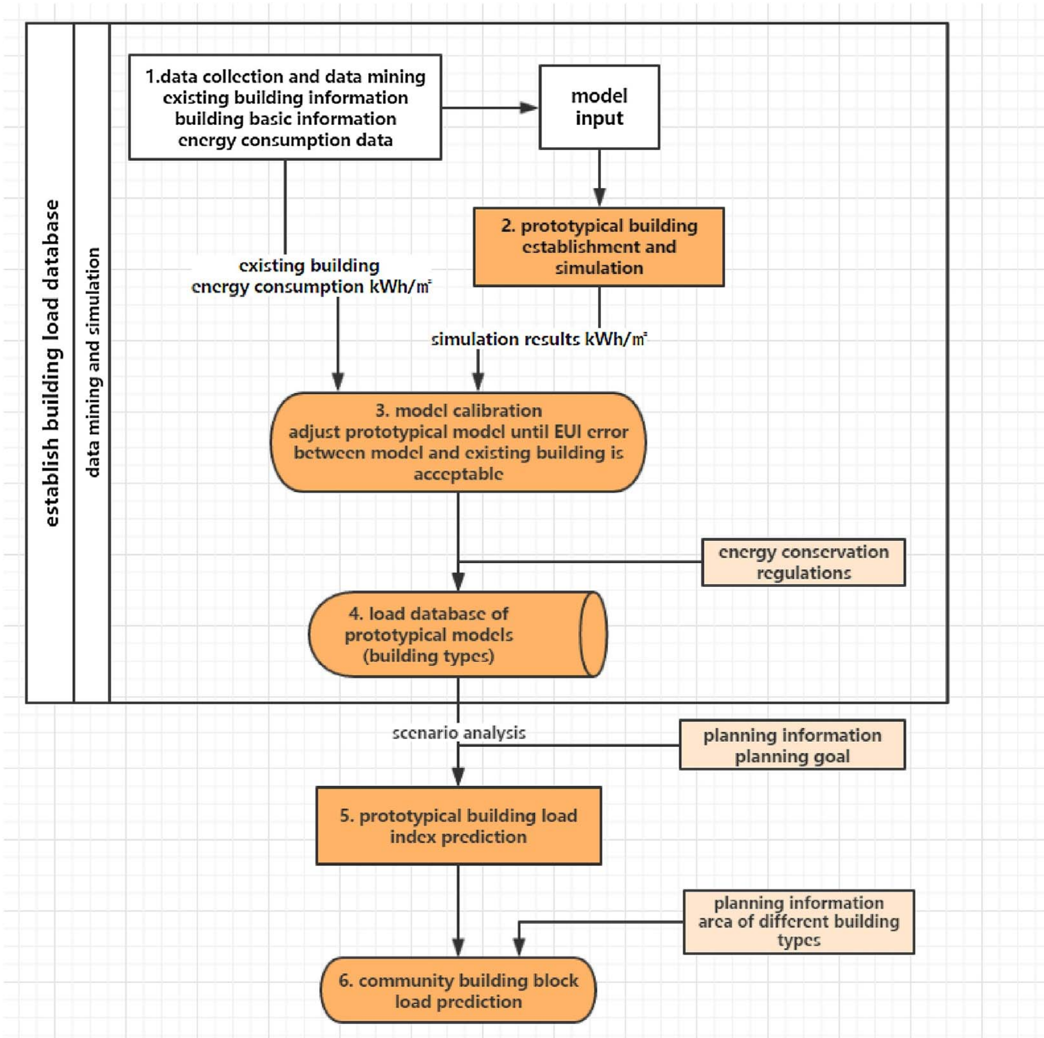


Fig. 6. Program of community load prediction tool.

Table 6
Building types and supply areas 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

Table 7
CBD's scenario settings.

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

calculated as follows.

$$\text{Part load ratio} = \frac{hourly\ load}{peak\ load} \tag{9}$$

Based on the load prediction results, the part load ratios and operation times of the energy stations are obtained; these are shown in Figs. 7 and 8.

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.

3.2. *Load leveling*

3.2.1. *Sample data*

In this study, three building types, i.e., offices, shopping malls, and hotels are considered. Assume that $a_i (0 \le a_i \le 1)$ is the building area ratio of each building type, and that a_i is a multiple of 0.1. For a specific community, the total building area ratio of different building types adds up to 1. Thus, there are 66 possible combinations (see Table 9). Then, the annual average daily loads of heating, cooling and electricity are obtained, whose standard deviations are calculated (see Table 9). With

Table 8
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

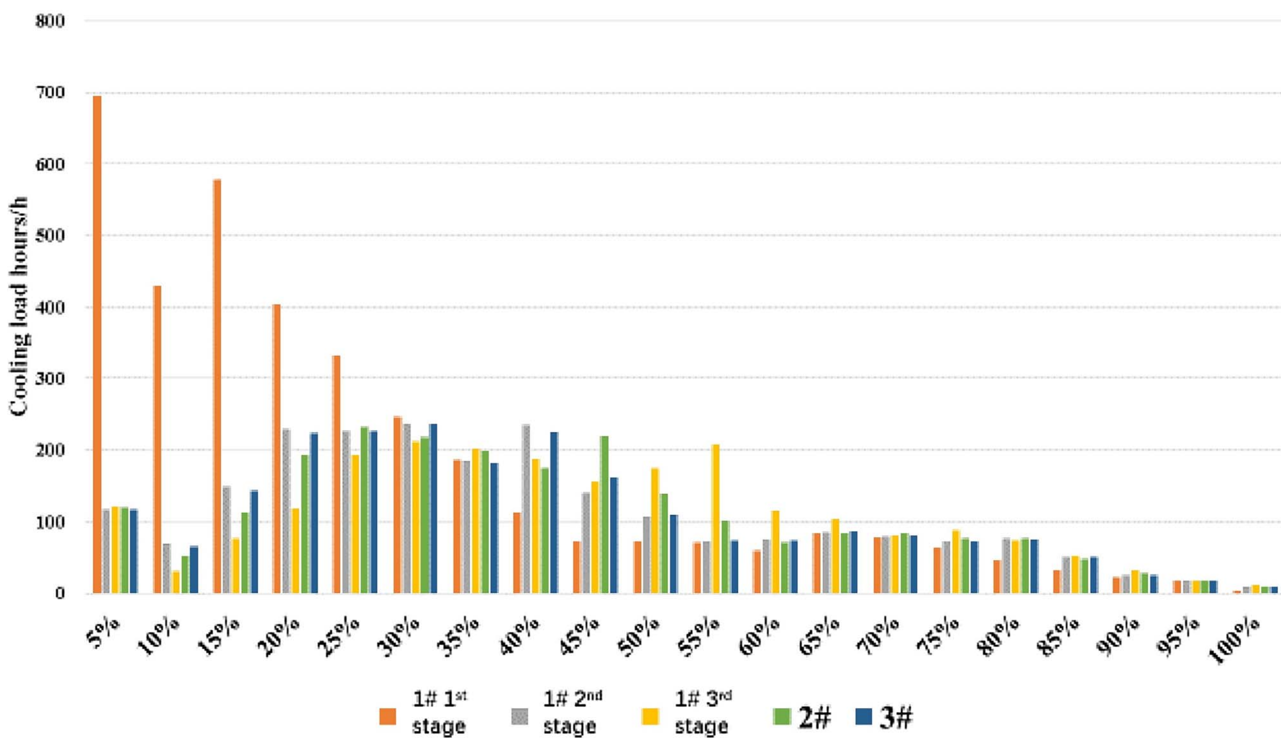


Fig. 7. Part load operation time in cooling season for each energy station.

these data, load leveling is conducted.

3.2.2. Load levelling analysis

With the above SD results, fuzzy clustering can be performed to categorize the results. Firstly, the SD results are normalized. For each of the three loads, a matrix is obtained where the data of each element are the normalized SD values. Then, similar matrices are built, and those who are closest in Euclidean distance are clustered into one category. All the results are clustered into three groups. The load leveling performance of the clustered group with the smallest SD value (i.e., the group with the smoothest and most stable load profile) is considered to be good. Similarly, the group with the largest SD value is considered to have poor performance, and the remaining group is considered to have a fair load leveling performance.

The integrated clustering results and load leveling assessments are presented in Table 10.

Because there are three assessing categories and three load profiles in each building area ratio combination, there are totally nine types of assessments. As can be seen from Table 10, Sample 26 (Office: 0.4, Shopping mall: 0.2, and Hotel: 0 4 and Sample 27 Office: 0 5, Shopping mall: 0 2, and Hotel: 0 3 show the best load leveling performance Thus, the CBD's building area ratio may be close to that of Sample 26 or Sample 27.

Using the evaluation results, the load leveling performance of the Hongqiao CBD can be assessed. The assessments are presented in Table 11.

From the above table, it is clear that the building area ratio in Hongqiao CBD can be optimized, especially the planning of energy station 1# at stage 3, which shows poor load leveling performance in both cooling load and electricity load. The building area ratio may be adjusted based on the results of load leveling. However, the building area ratio is closely related to the function and development of the community, and hence it should be decided after considering all these influencing factors. The building area ratios suggested in this study can be considered only as a reference.

3.3. Optimization of energy configuration

In this section, the energy configuration for optimal economic performance is obtained using DER-CAM. Moreover, optimization of energy configuration is conducted for the cases where the building ratios are adjusted according to the load leveling suggestion given in Section 3.2. Optimization of energy station 1# is presented as an illustration.

3.3.1. Input data

As per the original plan, the building area ratio in Energy Station 1#

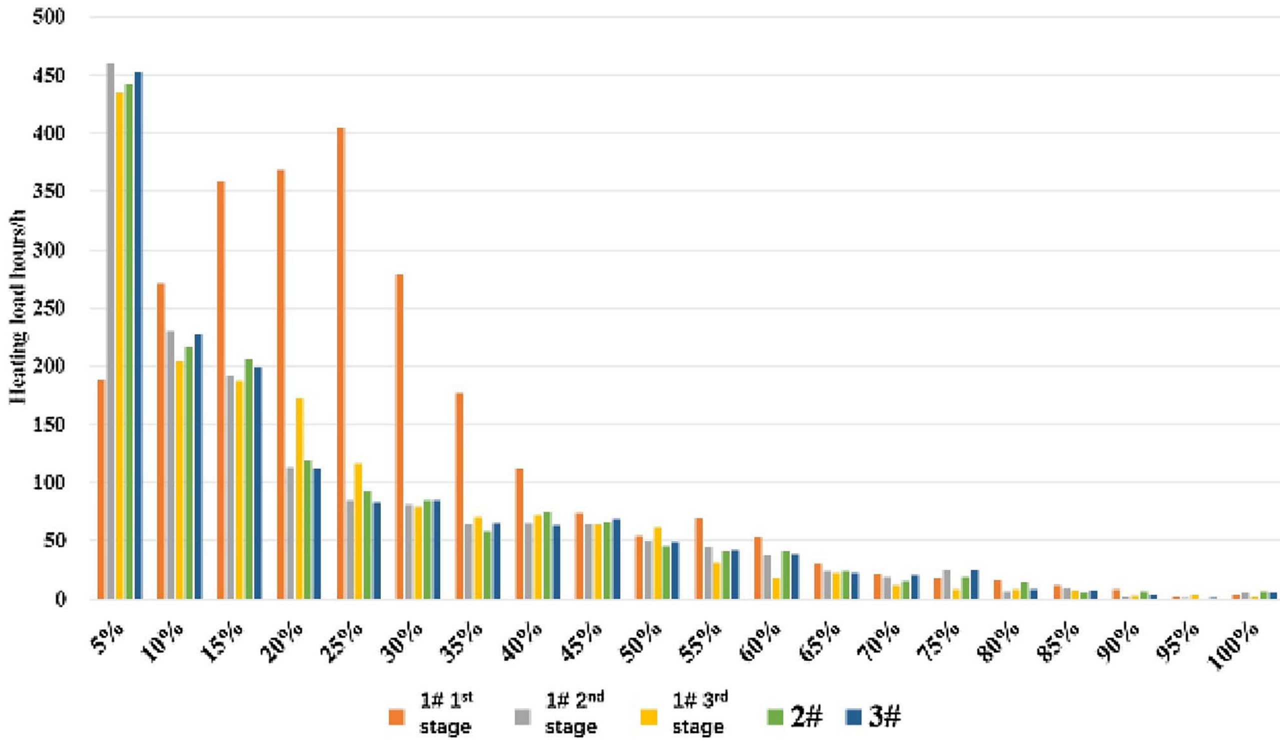


Fig. 8. Part load operation time in heating season for each energy station.

for offices, shopping mall, and hotel is [0.5, 0.4, 0.1]. According to the suggested building area ratios whose load leveling performances are the best across all the three load types, the building area ratio of [0.5, 0.2, 0.3] is chosen as the case for comparison. In the two comparative cases, the total building area is the same (see Table 12).

The annual loads of both cases are calculated. According the input requirement of DER-CAM, the load profiles are divided into weekday load, weekend load, and peak day load. The price of natural gas in

Table 9
Building area ratio combinations and standard deviation [Office: Shopping mall: Hotel].

Building area ratio	SD-cooling W/m^2	SD-heating W/m^2	SD-electricity W/m^2	Building area ratio	SD-cooling W/m^2	SD-heating W/m^2	SD-electricity W/m^2
1[0,0,1]	8.86	6.33	7.75	34[0.3,0.3,0.4]	13.46	3.66	6.18
2[0.1,0,0.9]	8.24	5.82	6.87	35[0.4,0.3,0.3]	13.88	3.7	6.05
3[0.2,0,0.8]	7.81	5.38	6.05	36[0.5,0.3,0.2]	14.42	3.91	6.1
4[0.3,0,0.7]	7.62	5.03	5.32	37[0.6,0.3,0.1]	15.07	4.26	6.34
5[0.4,0,0.6]	7.68	4.79	4.73	38[0.7,0.3,0]	15.81	4.71	6.74
6[0.5,0,0.5]	7.98	4.66	4.31	39[0,0.4,0.6]	14.95	3.94	7.72
7[0.6,0,0.4]	8.49	4.67	4.14	40[0.1,0.4,0.5]	15.06	3.61	7.26
8[0.7,0,0.3]	9.19	4.82	4.24	41[0.2,0.4,0.4]	15.3	3.43	6.93
9[0.8,0,0.2]	10.04	5.08	4.6	42[0.3,0.4,0.3]	15.66	3.42	6.75
10[0.9,0,0.1]	10.99	5.45	5.15	43[0.4,0.4,0.2]	16.13	3.6	6.75
11[1,0,0]	12.02	5.9	5.85	44[0.5,0.4,0.1]	16.7	3.93	6.91
12[0,0.1,0.9]	9.88	5.67	7.53	45[0.6,0.4,0]	17.37	4.38	7.22
13[0.1,0.1,0.8]	9.51	5.19	6.74	46[0,0.5,0.5]	16.98	3.5	8.05
14[0.2,0.1,0.7]	9.33	4.79	6.03	47[0.1,0.5,0.4]	17.19	3.26	7.7
15[0.3,0.1,0.6]	9.36	4.49	5.43	48[0.2,0.5,0.3]	17.5	3.21	7.49
16[0.4,0.1,0.5]	9.59	4.32	5	49[0.3,0.5,0.2]	17.91	3.34	7.43
17[0.5,0.1,0.4]	10.01	4.3	4.77	50[0.4,0.5,0.1]	18.42	3.65	7.52
18[0.6,0.1,0.3]	10.6	4.41	4.77	51[0.5,0.5,0]	19.01	4.09	7.76
19[0.7,0.1,0.2]	11.32	4.66	5.01	52[0,0.6,0.4]	19.1	3.18	8.49
20[0.8,0.1,0.1]	12.16	5.02	5.45	53[0.1,0.6,0.3]	19.37	3.07	8.25
21[0.9,0.1,0]	13.09	5.48	6.04	54[0.2,0.6,0.2]	19.74	3.16	8.15
22[0,0.2,0.8]	11.32	5.05	7.46	55[0.3,0.6,0.1]	20.19	3.43	8.18
23[0.1,0.2,0.7]	11.15	4.6	6.76	56[0.4,0.6,0]	20.73	3.85	8.35
24[0.2,0.2,0.6]	11.16	4.25	6.17	57[0,0.7,0.3]	21.28	3.02	9.03
25[0.3,0.2,0.5]	11.35	4.03	5.72	58[0.1,0.7,0.2]	21.61	3.06	8.89
26[0.4,0.2,0.4]	11.69	3.95	5.45	59[0.2,0.7,0.1]	22.01	3.29	8.87
27[0.5,0.2,0.3]	12.18	4.04	5.38	60[0.3,0.7,0]	22.5	3.68	8.98
28[0.6,0.2,0.2]	12.8	4.27	5.52	61[0,0.8,0.2]	23.5	3.05	9.64
29[0.7,0.2,0.1]	13.54	4.63	5.85	62[0.1,0.8,0.1]	23.87	3.23	9.59
30[0.8,0.2,0]	14.37	5.08	6.35	63[0.2,0.8,0]	24.31	3.58	9.65
31[0,0.3,0.7]	13.04	4.46	7.52	64[0,0.9,0.1]	25.75	3.26	10.32
32[0.1,0.3,0.6]	13.04	4.06	6.94	65[0.1,0.9,0]	26.16	3.55	10.34
33[0.2,0.3,0.5]	13.18	3.78	6.48	66[0,1,0]	28.03	3.61	11.06

Table 10
Evaluation results of cooling, heating and electricity load leveling performance [Office: Shopping mall: Hotel].

Sample	Cooling load	Heating load	Electricity load	Sample	Cooling load	Heating load	Electricity load
1.[0,0,1]	good	poor	fair	34.[0.3,0.3,0.4]	good	good	fair
2.[0.1,0,0.9]	good	poor	fair	35.[0.4,0.3,0.3]	good	good	fair
3.[0.2,0.0,0.8]	good	fair	fair	36.[0.5,0.3,0.2]	good	good	fair
4.[0.3,0.0,0.7]	good	fair	good	37.[0.6,0.3,0.1]	good	fair	fair
5.[0.4,0.0,0.6]	good	fair	good	38.[0.7,0.3,0.0]	good	fair	fair
6.[0.5,0.0,0.5]	good	fair	good	39.[0.0,0.4,0.6]	good	good	fair
7.[0.6,0.0,0.4]	good	fair	good	40.[0.1,0.4,0.5]	good	good	fair
8.[0.7,0.0,0.3]	good	fair	good	41.[0.2,0.4,0.4]	good	good	fair
9.[0.8,0.0,0.2]	good	fair	good	42.[0.3,0.4,0.3]	good	good	fair
10.[0.9,0.0,0.1]	good	fair	good	43.[0.4,0.4,0.2]	good	good	fair
11.[1.0,0.0,0.0]	good	poor	fair	44.[0.5,0.4,0.1]	fair	good	fair
12.[0.0,0.1,0.9]	good	poor	fair	45.[0.6,0.4,0.0]	fair	fair	fair
13.[0.1,0.1,0.8]	good	fair	fair	46.[0.0,0.5,0.5]	fair	good	poor
14.[0.2,0.1,0.7]	good	fair	fair	47.[0.1,0.5,0.4]	fair	good	fair
15.[0.3,0.1,0.6]	good	fair	good	48.[0.2,0.5,0.3]	fair	good	fair
16.[0.4,0.1,0.5]	good	fair	good	49.[0.3,0.5,0.2]	fair	good	fair
17.[0.5,0.1,0.4]	good	fair	good	50.[0.4,0.5,0.1]	fair	good	fair
18.[0.6,0.1,0.3]	good	fair	good	51.[0.5,0.5,0.0]	fair	good	fair
19.[0.7,0.1,0.2]	good	fair	good	52.[0.0,0.6,0.4]	fair	good	poor
20.[0.8,0.1,0.1]	good	fair	good	53.[0.1,0.6,0.3]	fair	good	poor
21.[0.9,0.1,0.0]	good	fair	fair	54.[0.2,0.6,0.2]	fair	good	poor
22.[0.0,0.2,0.8]	good	fair	fair	55.[0.3,0.6,0.1]	fair	good	poor
23.[0.1,0.2,0.7]	good	fair	fair	56.[0.4,0.6,0.0]	poor	good	poor
24.[0.2,0.2,0.6]	good	fair	fair	57.[0.0,0.7,0.3]	poor	good	poor
25.[0.3,0.2,0.5]	good	good	fair	58.[0.1,0.7,0.2]	poor	good	poor
26. [0.4,0.2,0.4]	**good**	**good**	**good**	59.[0.2,0.7,0.1]	poor	good	poor
27. [0.5,0.2,0.3]	**good**	**good**	**good**	60.[0.3,0.7,0.0]	poor	good	poor
28.[0.6,0.2,0.2]	good	fair	good	61.[0.0,0.8,0.2]	poor	good	poor
29.[0.7,0.2,0.1]	good	fair	fair	62.[0.1,0.8,0.1]	poor	good	poor
30.[0.8,0.2,0.0]	good	fair	fair	63.[0.2,0.8,0.0]	poor	good	poor
31.[0.0,0.3,0.7]	good	fair	fair	64.[0.0,0.9,0.1]	poor	good	poor
32.[0.1,0.3,0.6]	good	good	fair	65.[0.1,0.9,0.0]	poor	good	poor
33.[0.2,0.3,0.5]	good	good	fair	66.[0.0,1.0,0.0]	poor	good	poor

Bold value in this table means that these two building area ratios are recommended because they show good load leveling performance.

Table 11
Load leveling performance of Hongqiao CBD.

Energy Station	Project progress	Office ratio	Shopping mall area ratio	Hotel ratio	Assessment
1#	Stage 1	0.6	0	0.4	Cooling load: good, Heating load: fair, Electricity load: good
	Stage 2	0.6	0.4	–	Cooling load: fair, Heating load: fair, Electricity load: fair
	Stage 3	0.4	0.6	–	Cooling load: poor, Heating load: good, Electricity load: poor
2#		0.5	0.5	–	Cooling load: fair, Heating load: good, Electricity load: fair
3#		0.6	0.4	–	Cooling load: fair, Heating load: fair, Electricity load: fair

Table 12
Comparison of original and adjusted cases.

Case	Office (m^2)	Shopping mall (m^2)	Hotel (m^2)	Total (m^2)	Building area ratio [office: shopping mall: hotel]	Assessment
Original	479,387	385,308	98,106	962,800	[0.5, 0.4, 0.1]	Cooling load: Fair, Heating load: Good, Electricity load: Fair
Adjusted	481,400	192,560	288,840	962,800	[0.5, 0.2, 0.3]	Cooling load: Good, Heating load: Good, Electricity load: Good

Shanghai is \$0.47/m^3, and the time-of-use electricity price is presented in Table 13.

The commonly used equipment's cost, maintenance cost, and parameters are investigated (Feng et al., 2012) and listed in Tables 14–16.

3.3.2. Results of energy system configuration

Optimization of energy system configuration for both cases is conducted using DER-CAM by solving for the optimal economic performance. The calculated results of equipment capacity, energy consumption, and total cost are listed in Tables 17 and 18.

Table 13
Time-of-use electricity price.

Summer	Time period	Summer price [\$/kWh]	Non-summer price [\$/kWh]
Peak time	8:00–11:00 18:00–21:00	0.1805	0.1754
Flat time	6:00–8:00 11:00–18:00 21:00–22:00	0.1114	0.1062
Valley time	22:00–6:00	0.0431	0.0527

Table 14
Initial investment cost of equipment.

	Generator ($/kW)	Gas boiler ($/kW)	Absorption chiller ($/kW)	Electricity chiller ($/kW)	Heat pump ($/kW)
Equipment investment cost	367.85	29.43	132.43	103	103

Table 15
Maintenance cost.

Equipment	Fixed cost ($/kW)	Variable cost ($/kW)
Generator	0	0.0145
Gas boiler	0.3016	0
Absorption chiller	1.8245	0
Electric chiller	0.1824	0
Heat pump	0.1824	0

Table 16
Equipment parameters.

Equipment	Parameter	Value	Life cycle (years)
Generator	Efficiency	0.3	20
	Heat-power ratio	1.48	
Gas boiler	Efficiency	0.9	20
Absorption chiller	Cooling COP	1.2	15
	Heating COP	0.9	
Electric chiller	Cooling COP	5.5	20
Heat pump	Heating COP	5.0	10
	Cooling COP	4.8	

Table 17
Comparison of equipment configuration.

Equipment	Original capacity (kW)	Adjusted capacity (kW)
Internal combustion engine	25,000.00	25,000.00
Heat pump-cooling	309,510.30	280,430.70
heating	322,406.50	292,115.30
Absorption chiller	55,774.60	46,741.30

Table 18
Annual energy consumption and cost comparison.

Case	Electricity consumption (kWh/year)	Natural gas consumption (kWh/year)	Total cost ($)
Original	75,778,026.80	185,926,691.80	21,916,940
Adjusted	69,453,575.60	157,407,890.20	18,684,754

The results reveal that the adjusted case requires lower equipment capacity. Besides, the load profiles of the adjusted case are more stable and better leveled, and the equipment operates at higher efficiency; this contributes to a reduction in both electricity and natural gas consumption.

3.3.3. *Influence of load leveling on energy system configuration*

1) Influence on system capacity

The peak loads of cooling, heating and electricity are listed in Table 19:

It can be seen from the table that after the adjustment, the peak loads of cooling, heating, and electricity change. The peak load of cooling reduces by 10.24%, while that of electricity reduces by 16.88%.

Table 19
Peak load comparison.

Case	Peak cooling load (kW)	Peak heating load (kW)	Peak electricity load (kW)
Original	81689	32174	19907
Adjusted	73325	36918	16524

The peak load of heating increases by 12.85%. In the adjusted case, the capacity of the heat pump is 9.4% lower than that of the original case, while the capacity of the absorption chiller is 16.2% lower. Thus, load leveling affects the peak loads, which further influences the system capacity. The more leveled the loads are, the smaller the capacity required is.

2) Influence on energy consumption

The adjusted case of energy station 1# shows 15.34% less usage of natural gas and 8.35% less usage of electricity, which means 14.75% cost saving compared with the original case. As the hourly load profile changes influence the system operation, energy consumption and cost vary. Equipment can operate at higher efficiency, which leads to energy conservation. Besides, after the building area ratio adjustment, the heat-to-power ratio is different, and hence the system equipment specification may also vary.

4. Conclusions and future work

1. Given that community energy planning involves many uncertainties, an integrated method of load prediction in buildings is proposed, which combines building simulation and scenario analysis.
2. Prototypical models of office, shopping mall, and hotel buildings in Shanghai are built and calibrated. Using the proposed method and scenario analysis, a load index database of various prototypical buildings is obtained. Based on this database, a quick calculation tool for community load prediction is developed; this tool is used to predict cooling, heating, and electricity loads of a CBD in Shanghai.
3. By adjusting the area ratios of different building types in the community, the load profile could be changed. Further, load leveling is defined, and the standard deviation of the load profile is used to evaluate its performance. Fuzzy clustering of cooling, heating, and electricity loads is conducted to categorize the load leveling performance of each combination of building area ratios.
4. Suggestions on the community's building area ratio selection are given. The area ratios of [0.4, 0.2, 0.4] and [0.5, 0.2, 0.3] for offices, shopping malls, and hotels show the best load leveling performance.
5. Optimization of energy configuration of the original plan and the adjusted plan is conducted to find out the influence of load leveling. The results show that adjustment of building area ratio to optimize load leveling and energy configuration can not only improve the energy efficiency of the community energy system, but also lead to better economic performance.

Despite the merits of this study, some problems still exist, which need to be tackled. Firstly, owing to lack in data of higher resolution, the validation of prototypical models is not precise enough. With the accumulation of data on energy consumption platform of China's public buildings, this problem can be solved in the future. Secondly, regional microclimate creates uncertainties on the community's building load, and at the planning stage, parameters like building form are not determined. Thus, the effects of microclimate on building load can hardly be studied by modeling. It is still not known how to quantify the impacts of microclimate. In the economic performance analysis, the building's location, construction cost, and distribution cost are not considered; these aspects require further study.

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