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Using Residential and Office Building Archetypes for Energy Efficiency Building Solutions in an Urban Scale: A China Case Study

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Abstract: Building energy consumption accounts for 36% of the overall energy end use worldwide and is growing rapidly as developing countries continue to urbanize. Understanding the energy use at urban scale will lay the foundation for identification of energy efficiency opportunities to be deployed at speed. China has almost half of global new constructions and plays an important role in building suitability. However, an open source national building energy consumption database is not available in China. To provide data support for building energy consumptions, this paper used a simulation method to develop an urban building energy consumption database for a pilot city in Wuhan, China. First, residential, small, and large office building archetype energy models were created in EnergyPlus to represent typical building energy consumption in Wuhan. The baseline reference model simulation results were further validated using survey data from the literature. Second, stochastic simulations were conducted to consider different design parameters and occupants' energy usage intensity scenarios, such as thermal properties of the building envelope, lighting power density, equipment power density, HVAC (heating, ventilation and air conditioning) schedule, etc. A building energy consumption database was generated for typical building archetypes. Third, data-driven regression analysis was conducted to support quick building energy consumption prediction using key high-level building information inputs. Finally, a web-based urban energy platform and an interface were developed to support further third-party application development. The research is expected to provide fast energy efficiency building design solutions for urban planning, new constructions as well as building retrofits.

Keywords: urban scale; building energy simulation; EnergyPlus; regression; building archetypes

1. Introduction

By 2050, 66% of the world's population will live in urban areas [1], making urbanization one of the critical themes and challenges in this century. This is the case especially for some Asian countries, such as China, where city boundaries are expanding with numerous new constructions every year. China has contributed to approximately 50% of the world's new constructions since 2010 [2]. Rapid global urbanization has resulted in significant increases in energy consumption, greenhouse gas emissions, pollutant emissions, and widespread environmental degradation. Urban areas account for 67–76% of global energy use and 71–76% of CO_2 emissions [3]. Cities around the world are searching for strategies to reduce energy consumption and to become green and low-carbon cities, and enhance their resilience in a changing climate.

Building energy consumption accounts for 36% of the global final energy use in 2017, and this number is much higher in urban areas [4,5]. In the U.S., national level building energy consumption databases have been developed and regularly updated to represent actual building energy usage levels. For example, the Residential Energy Consumption Survey (RECS) and Commercial Buildings Energy Consumption Survey (CBECS) collect energy-related building characteristics and energy usage information [6,7]. However, this kind of open source national building energy consumption database is not available in China.

To better understand building energy consumption in urban areas, besides survey and measurement, urban datasets and urban-scale building energy consumption platforms have been developed based on urban-scale building energy simulations. Urban-scale building energy simulation can play an essential role in sustainable urbanization, allowing planners and policy makers to develop planning strategies using the lens of energy performance.

A research group from the college of Architecture at Georgia Institute of Technology developed a GIS-based urban building energy modeling system, called Urban-EPC. It includes four main models: the Data Preparation Model, the Pre-Simulation Model, the Main Simulation Model and the Visualization and Analysis Model. This Urban-EPC tool also uses physics models and calculates the hourly heat balance of the whole building. It contains three categories of building vintage (based on the construction year), each of which includes 16 building types representing most of the commercial buildings across 16 US climate zones. The development team also conducted a case study for Manhattan. They obtained the building footprint data from New York city planning database with references to Google Earth 3D building [8].

The sustainable design lab at Massachusetts Institute of Technology (MIT) also developed an Urban Building Energy Model (UBEM) for Boston to estimate citywide hourly energy demands at the building level. In this project, the geometric input for Boston was also extracted from GIS shapefiles into the Rhinoceros 3D V5 CAD environment, and a total of 76 different building archetypes were then assigned to individual buildings based on land use and building age. Bayesian calibration was applied to update the probability distributions of uncertain parameters in archetype descriptions using monthly and annual measured energy usage data. EnergyPlus was used to simulate the energy consumption results of individual building models. The urban energy use pattern of different times of the day is visualized and overlaid with the Boston map. The tool can help local communities to evaluate energy related decisions and building retrofit strategies to reduce building energy use. They also predicated future scenarios, including solar photovoltaic (PV) penetration, and demand response strategy implantation [9,10].

Lawrence Berkeley National Laboratory (LBNL) developed and released a web-based urban-scale building stock simulation platform, called City Building Energy Saver (CityBES). It is designed to support building retrofit analysis. CityBES uses an open standard, CityGML, to represent the 3D city models, and then it categorizes buildings into different types, including small/medium/large offices, hotels, schools, and hospitals. For each type of these buildings, CityBES generates baseline EnergyPlus simulation models based on the cities' building datasets and user-selected energy conservation measures (ECMs). There are three main layers: the data layer, the simulation algorithms and software tools layer, and the use-cases layer. The neighborhood buildings in CityBES are modeled as shading surfaces in EnergyPlus to consider the shading interactions between buildings. Simulation results, such as energy use intensity (EUI), can be color-coded and mapped to the 3D buildings with the GIS database. A case study using CityBES for San Francisco shows a potential retrofit site energy saving of 23–38% per building [11].

In addition, the Oak Ridge National Laboratory and National Renewable Energy Laboratory have also developed urban scale simulation tools, called AutoBEM and URBANopt, respectively [12,13]. They used similar approaches: generate baseline building energy models for each building type as a template, categorize buildings in the area of interest into corresponding archetype and link to the template results, map the simulation results to a GIS platform for visualization. This method can provide quick design support for large scale energy decision making based on archetype data, without running detailed building energy simulation.

However, the above case studies are based mainly on simulation results. It is important to validate the numerical simulations using ground truth building energy survey data and consider occupants' energy usage behavior. Furthermore, the case studies are for large cities in the US, where rapid urbanization has almost been completed. Due to rapid urbanization, China has a large percentage of new constructions. Meanwhile, old buildings with different years of building exist in the same urban region. The building age variation could be as high as several decades. As they were subject to different building design standards/codes, the same type of building, if built in different years, could show very different building consumption profiles. Therefore, building vintage is a key parameter to consider. However, open-source building energy models for typical archetypes have not been well developed in China. It is important to develop an updated urban-scale building energy consumption platform for China, to understand both the spatial and temporal urban energy system.

This paper shows our efforts on building archetype development for the urban energy simulation platform. Three main archetype buildings (residential building, small office building, and large office building) are created and demonstrated in this paper with the following innovations.

- Develop reference building energy models for residential, small office, and large office building types in Wuhan, China, considering different vintages and unique HVAC usage patterns
- Create an application programming interface (API) for Wuhan to support urban building energy platform development.

2. Reference Building Models

Currently, there are no open sourced well-developed reference building models in China. Residential and office building are selected for prototype development in this paper because these two types of buildings are the top two largest building stocks in China, with a percentage of 73% and 9%, respectively [14].

Working with local project partners, the most popular configurations and geometries for residential buildings as well as office buildings were collected through a survey. Figure 1 shows the geometry of a typical residential building. It is a 10-story apartment building with a total building area of 7836 m^2. According to the different orientation, each floor is divided into nine thermal zones: eight apartment units, and one corridor. The floor area of each apartment is about 88 m^2.

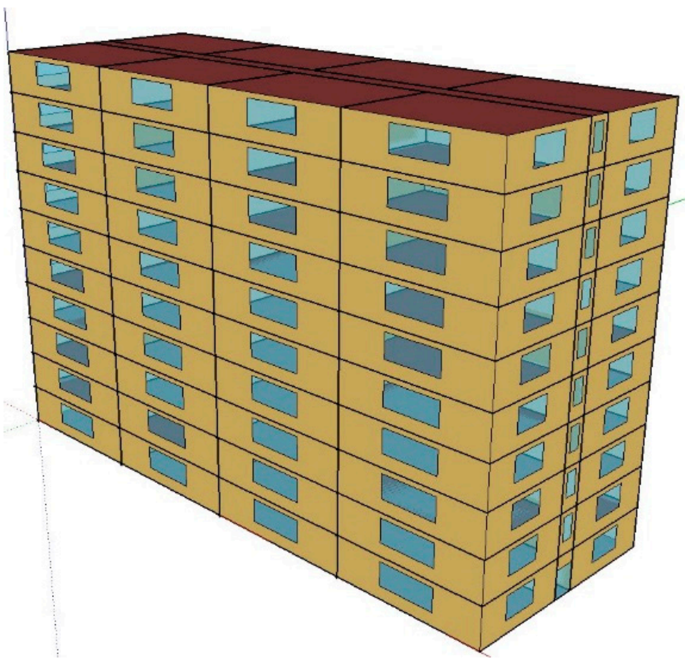

Figure 1. Geometry of the residential reference building.

Figure 2 shows the most popular geometries of a typical small office building (left) and a large office building (right). The small office building has three floors and the large office has eighteen floors. Each floor has four external zones and one core zone. The total building areas are 8176 m^2 for the small office and 26,142 m^2 for the large office, respectively.

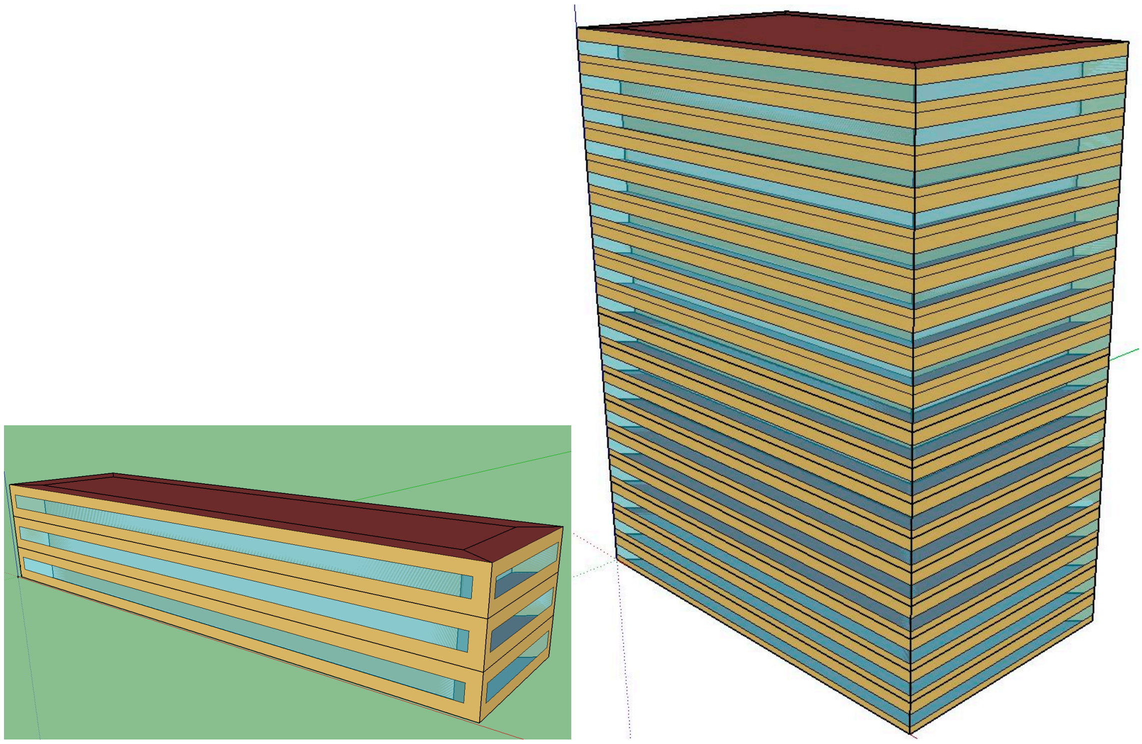

Figure 2. Geometries of reference office buildings (left: small office, right: large office).

Key building design parameters, such as the building envelope's thermal properties, lighting power density, equipment load density, HVAC system and schedules, were defined based on the corresponding residential and commercial building design standards [15,16].

Based on the survey, the HVAC systems for these three building types are different. Residential and small office buildings use ductless mini-split heat pumps for heating and cooling, while large office buildings use chillers and cooling towers for cooling and boilers for heating.

To capture the average energy usage level, the China Residential Energy Consumption Survey (CRECS) data were used to determine the heating and cooling schedules for residential and small office building. The CRECS was conducted by Renming University in 2012. The CRECS2012 includes residential appliance usage and electricity consumption data from 1450 residential buildings across 26 provinces in China [17]. Valid instances numbering 218 from the hot summer and cold winter climate zone (where Wuhan is located) were used to calibrate the baseline residential model. Figure 3 shows the number of heating days in winter and the number of cooling days in summer, respectively. It can be observed that most people only use heating for less than one month in winter, and use cooling for one to two months in summer. Compared with cooling, the residents seem to be more tolerant of heating. Figure 4 shows the daily distribution of heating and cooling hours. It shows that most people use heating or cooling for less than 5 h per day. The heating and cooling schedules (days/year and hours/day) as well as the temperature setpoints of the reference buildings were adjusted to be the average values according to the survey data.

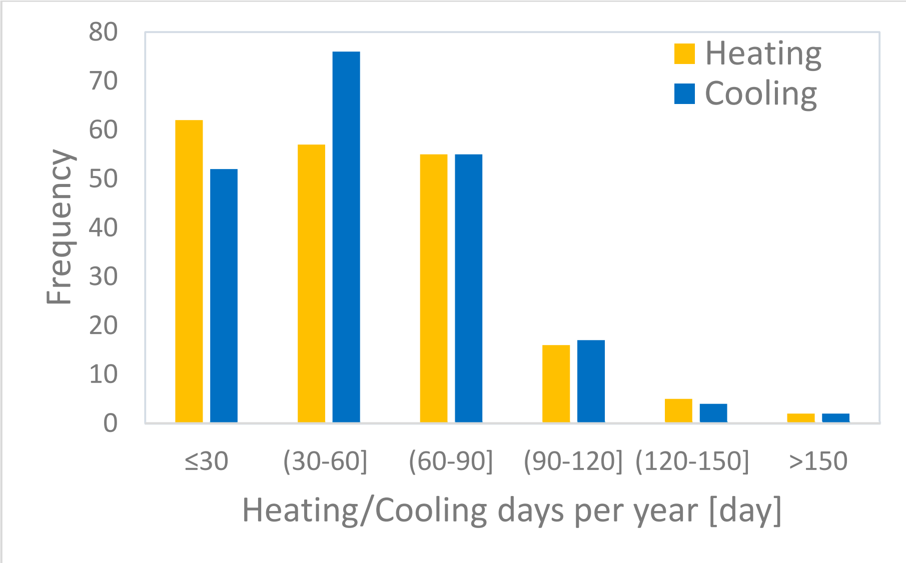

Figure 3. Distribution of heating/cooling days per year in winter/summer.

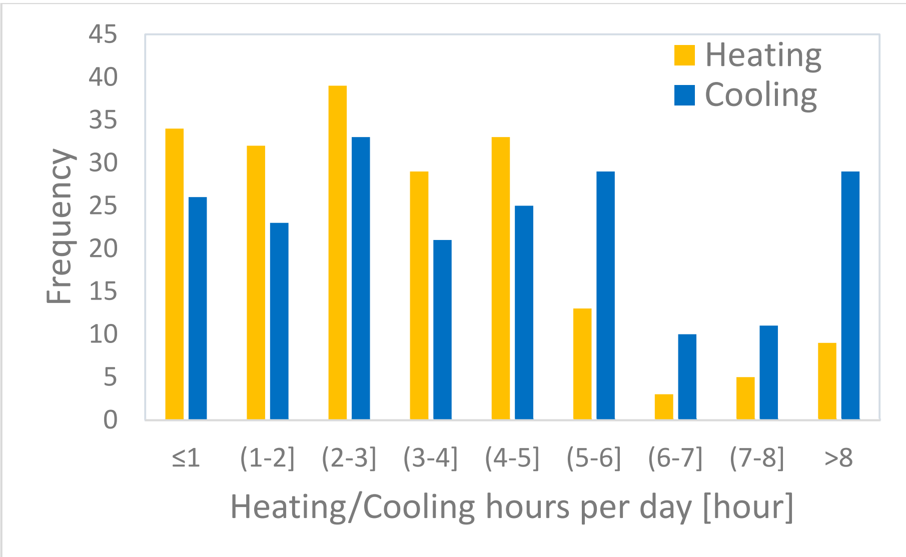

Figure 4. Distribution of heating/cooling hours per day in winter/summer.

The baseline reference buildings were developed using EnergyPlus software. EnergyPlus is an open source simulation engine for whole building energy consumption [18]. It was developed and is supported by the U.S. Department of Energy. EnergyPlus has been widely used and validated by researchers and designers. It is a console-based program, not a user interface. Some graphical interfaces for EnergyPlus, such as DesignBuilder and OpenStudio, are also available. Since the inputs and outputs for EnergyPlus are all text-based, users can easily edit the information to develop a customized system and run parametric simulations using scripts. The detail settings of each model are summarized in Table 1.

Table 1. Baseline EnergyPlus model settings.

Input Parameters	Unit	Small Office	Large Office	Residential Building	Reference
External wall insulation	W/m^2·K	0.597	0.597	0.88	Residential building: DB42T-559-2013 [10]; Small and large office buildings: GB50189-2015 [11]
Roof insulation	W/m^2·K	0.399	0.399	0.447	
Ground floor insulation	W/m^2·K	0.253	0.253	1.2	
External Windows	W/m^2·K	2.6	2.6	2.7	
Infiltration rate	ACH	1	1	1	
Lighting power dentistry	W/m^2	9	9	Apartment: 4.2, Corridor: 1.8	
Equipment power density	W/m^2	15	15	Plug load: 2, Kitchen: 5	
Occupancy density	m^2/person	10	10	2	
Infiltration rate	1/h	1.0	1.0	1.0	
HVAC system	-	Mini-split air conditioner	Chiller + Natural gas boiler	Mini-split air conditioner	Survey data [12]
Heating/Cooling setpoints	°C	20.5/23.5	20.5/23.5	18/26	
Heating Schedule	-	9:00–12:00, 1/1–2/14	8:00–15:00, 1/1–2/14	19:00–22:00, 1/1–2/14	
Cooling Schedule	-	12:00–16:00, 7/18–8/31	10:00–17:00, 7/18–8/31	18:00–22:00, 7/18–8/31	

Wuhan's hourly weather data were used to simulate annual building energy consumption [19]. Figure 5 shows the simulation results of a baseline residential building. The simulated total building electricity consumption is 27.8 kWh/m^2. It can be observed that heating and cooling energy consumptions only account for approximately 30% of the total annual electricity consumption. People tend to use the heat pumps only when the weather is too cold or too hot, to reduce their electricity bills. The occupants' behavioral energy saving patterns can be found.

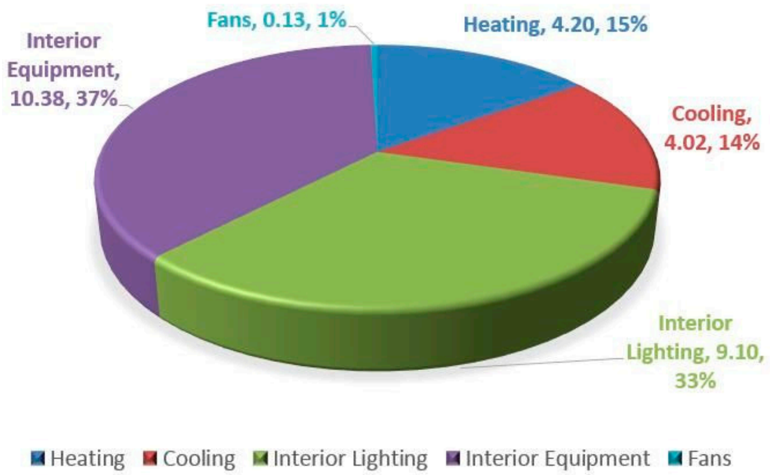

Figure 5. Reference residential building electricity consumption breakdown [kWh/m^2].

Figure 6 shows the distribution of electricity consumption in the hot summer and cold winter climate zone from the CRECS survey. The mean value (25.8 kWh/m^2) matches well with the EnergyPlus simulation result, which further validates the reference building model. It is of note that the electricity consumption is expected to be 35.3 kWh/m^2 (37% higher than the actual mean value) in the Guideline for Energy Consumption Quota of Civil Buildings in Wuhan [20]. Therefore, it is critical to consider occupants' energy use behavior and reflect the actual energy usage when making regional building energy consumption standards.

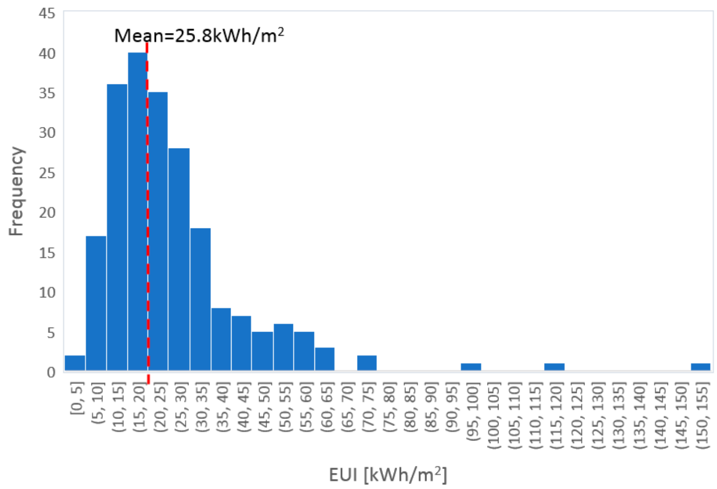

Figure 6. Distribution of electricity consumption from CRECS data.

Similarly, the HVAC schedules of small office and large office buildings were calibrated using the survey data. The annual energy consumptions were simulated in EnergyPlus. Figure 7 shows the simulation results. The total electricity consumption is 61.0 kWh/m^2 for the small office and 130.9 kWh/m^2 for the large office.

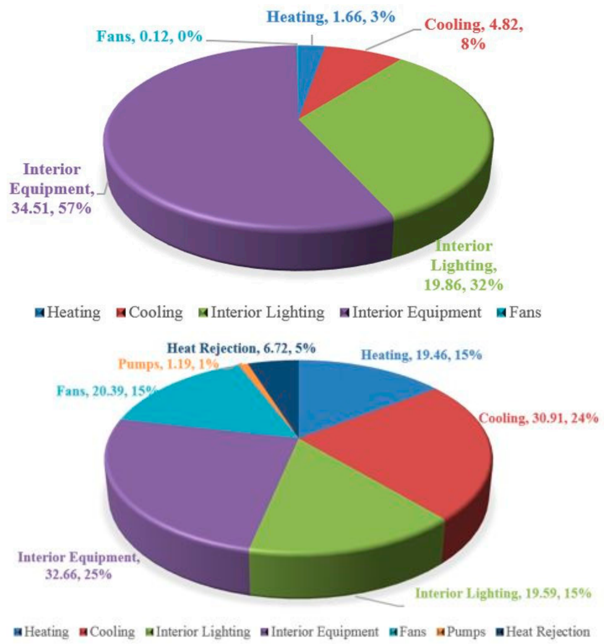

Figure 7. Reference office building electricity consumptions [kWh/m^2] (top: small office, bottom: large office).

3. Stochastic Simulations

After the reference building models were validated, stochastic simulations were conducted to consider different building design variations for the urban building energy consumption database development. Eight different design parameters, such as the building envelope's thermal properties, infiltration, heating and cooling schedules, lighting power density, and equipment power density, were considered to cover different constructions, building design scenarios and the occupant's energy usage patterns.

To differentiate building vintage, three levels (high, medium, and low) of building envelopes were studied by grouping U factors of different parts (external wall, slab, roof, and glass). The building geometry was kept constant to represent the most common configuration in Wuhan.

To reflect the actual energy saving behavior of the occupants and better capture different energy usage patterns, thirteen heating and cooling schedules were proposed. The schedule information was derived based on statistical analysis of the actual building energy data from CRECS. The data from the CRECS energy consumption survey was ranked from low to high. Level of 5% means the top 5% from the ranking. It represents the most efficient energy usage, in terms of heating and cooling hours per day and days per year. Level of 95% represents the least efficient energy usage (bottom 5% from the ranking). It is assumed that the lighting and plug/equipment loads are coupled with heating/cooling schedules, since people's energy saving behavior is consistent. Other energy usage profiles can be interpolated.

Figure 8 shows the stochastic cases of the residential building. In total, 117 design scenarios were considered. The combination of residential building baseline model is highlighted in yellow. In a similar way, 117 small office and 117 large office EnergyPlus models were generated to cover different energy use intensity scenarios for office buildings.

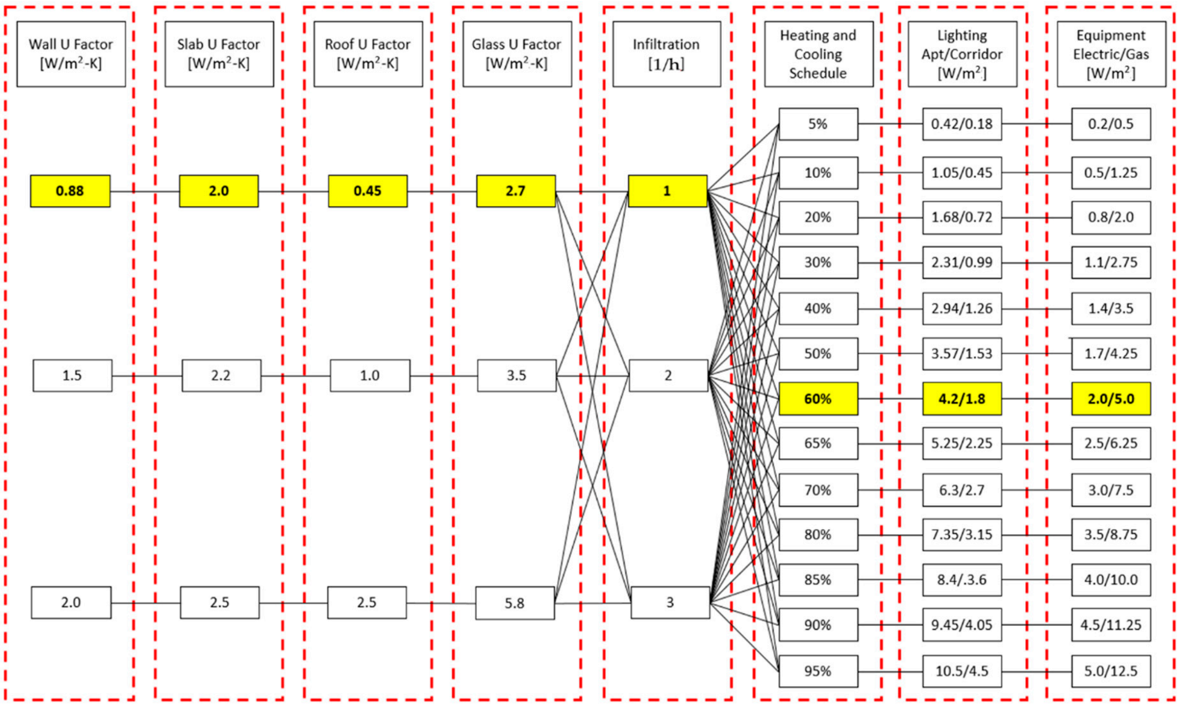

Figure 8. 117 stochastic scenarios of the residential building model.

4. Results and Discussion

Stochastic simulations were performed using EnergyPlus. Figure 9 shows the annual energy simulation results of residential buildings. It is of note that the energy consumptions are based on pure stochastic simulations defined in Section 3, assuming a uniform distribution of the 117 parametric design scenarios of each building type without any additional weighting factor. In reality, there may be less people in the very low (left) and very high (right) energy consumption ranges. To get a more realistic energy consumption distribution, we collected Wuhan's housing price (for residential building) and rent (for office building) information and adjusted the energy distribution accordingly. Figure 10 shows the housing price distribution of 18,864 residential buildings in Wuhan.

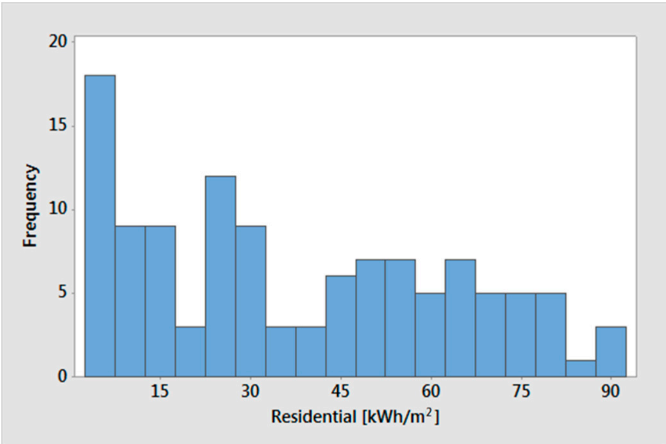

Figure 9. Annual residential building electricity consumption distribution of the stochastic simulations.

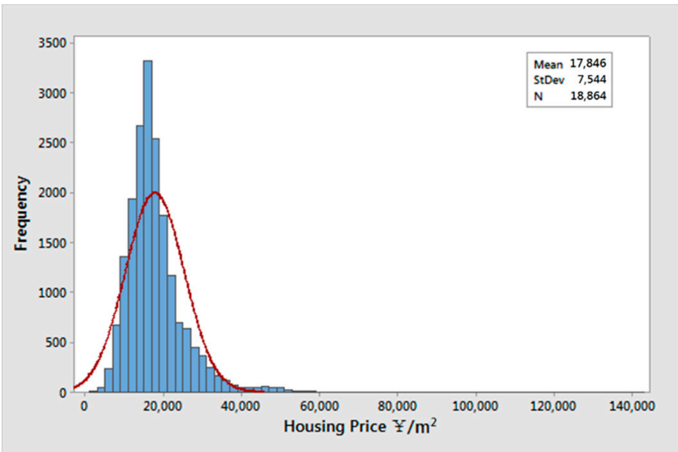

Figure 10. Housing price distribution of residential buildings in Wuhan.

Similarly, the annual electricity consumption distributions for small and large office buildings are shown in Figure 11.

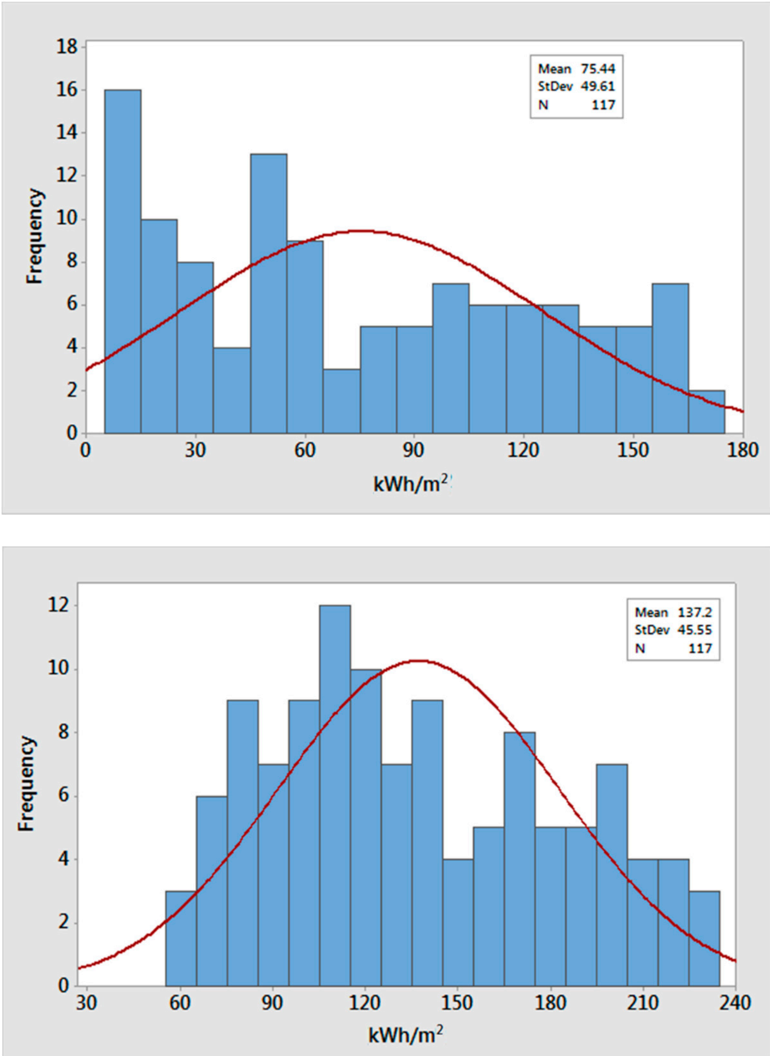

Figure 11. Annual office building electricity consumption distribution of the stochastic simulations (top: small office. Bottom: large office).

Furthermore, a data-driven regression model was developed to predict building energy consumption. Suggested by local urban planners and energy policy makers, building's price/rent and vintage were chosen to be the two key independent variables for the regression model.

Various machine learning algorithms were applied to the dataset to compare prediction accuracy. However, due to the very limited number of inputs, more complex algorithms did not show much advantage. Finally, linear regression models were selected, because of their robustness and high prediction accuracy. Tables 2–4 show the regression functions for residential, small office and large office buildings, respectively.

Table 2. Regression functions for residential buildings.

Item	Regression Function [kWh/m^2]	R^2
total electricity	$(0.0034 \times \text{price} - 29.2658) \times (1 + \text{F})$	0.93
heat electricity	$(0.0005 \times \text{price} - 3.4929) \times (1 + \text{F})$	0.77
cool electricity	$(0.0006 \times \text{price} - 5.4794) \times (1 + \text{F})$	0.92
light electricity	$(0.001 \times \text{price} - 9.406) \times (1 + \text{F})$	0.95
equip electricity	$(0.0013 \times \text{price} - 10.7288) \times (1 + \text{F})$	0.95
fan electricity	$(0.00005 \times \text{price} - 0.1587) \times (1 + \text{F})$	0.89
equip gas	$(0.0012 \times \text{price} - 9.941)$	0.95

where

$$F = \begin{cases} 0, & if\ year = 2010 \\ 0.0245, & if\ year = 2000 \\ 0.0603, & if\ year = 1990 \end{cases}$$

Table 3. Regression functions for small office buildings.

Item	Regression Function [kWh/m^2]	R^2
total electricity	$(2.2161 \times \text{rent} - 62.4217) \times (1 + \text{F})$	0.97
heat electricity	$\left(1.9 \times 10^{-5} \times \text{rent}^3 - 3.82 \times 10^{-5} \times \text{rent}^2 + 0.37 \times \text{rent} - 7.21\right) \times (1 + \text{F})$	0.81
cool electricity	$(0.2944 \times \text{rent} - 10.2555) \times (1 + \text{F})$	0.95
light electricity	$(0.7 \times \text{rent} - 19.4252) \times (1 + \text{F})$	0.97
equip electricity	$(1.2163 \times \text{rent} - 33.7546) \times (1 + \text{F})$	0.97
fan electricity	$(0.0057 \times \text{rent} - 0.1856) \times (1 + \text{F})$	0.96

where

$$F = \begin{cases} 0, & if\ year = 2010 \\ 0.0119, & if\ year = 2000 \\ 0.0228, & if\ year = 1990 \end{cases}$$

Table 4. Regression functions for large office buildings.

Item	Regression Function [kWh/m^2]	R^2
total electricity	$(1.4117 \times \text{rent} + 21.5392) \times (1 + F_{ele})$	0.86
heat electricity	$\left(10^{-6} \times \text{rent} - 7 \times 10^{-5}\right) \times (1 + F_{ele})$	0.88
cool electricity	$(0.0811 \times \text{rent} + 26.5387) \times (1 + F_{ele})$	0.83
light electricity	$(0.4711 \times \text{rent} - 11.3829) \times (1 + F_{ele})$	0.84
equip electricity	$(0.7851 \times \text{rent} - 18.9715) \times (1 + F_{ele})$	0.84
fan electricity	$(0.0549 \times \text{rent} + 18.6239) \times (1 + F_{ele})$	0.65
pump electricity	$(0.0027 \times \text{rent} + 1.0361) \times (1 + F_{ele})$	0.84
heatRej electricity	$(0.0169 \times \text{rent} + 5.6949) \times (1 + F_{ele})$	0.82
heat gas	$(0.0692 \times \text{rent} + 16.2071) \times \left(1 + F_{gas}\right)$	0.80

where

$$F_{ele} = \begin{cases} 0, & if\ year = 2010 \\ 0.0204, & if\ year = 2000 \\ 0.0245, & if\ year = 1990 \end{cases}, \quad F_{gas} = \begin{cases} 0, & if\ year = 2010 \\ 0.0544, & if\ year = 2000 \\ 0.0847, & if\ year = 1990 \end{cases}$$

To better illustrate our methods and make it easy and friendly to use, we developed a building simulation platform based on JavaEE technologies [8,9,21,22]. Figure 12 shows the system architecture. The platform consists of two parts. The first part is the service consumer (Application layer). The consumer here refers to the end users or any other third-party applications. The end user can utilize the service which results directly by opening a given service endpoint URL through the browser. Our service can also be incorporated into other external systems easily. The second part is the service provider. It generally includes three main layers: data layer, core algorithms implementation layer, and RESTful WebService layer. The data layer is responsible for providing enough data to make the platform work securely, such as the building information, system data, and stochastic simulation data.

Figure 13 shows how the simulation data is stored in the database. From the E-R diagram, we can see that hourly building energy consumptions can be simulated for the main types of buildings, such as large office, small office, and residential, in different scenarios. The core algorithm layer implements the core algorithms to simulate the building energy consumption. This layer mainly includes regression analysis and interpolation algorithms. To support third-party applications, our platform was designed to be a Service Oriented Architecture (SOA) based program [23]. Specifically, we chose the widely used RESTful WebService to wrap the core simulation APIs, so that everyone would be able to use our platform by just calling these standard WebServices [24]. For instance, users can use the API directly through their browsers by typing into the service endpoint as shown in Figure 14. In addition, third-party applications written in any programming languages can incorporate the APIs easily as these APIs are developed using the standard WebService.

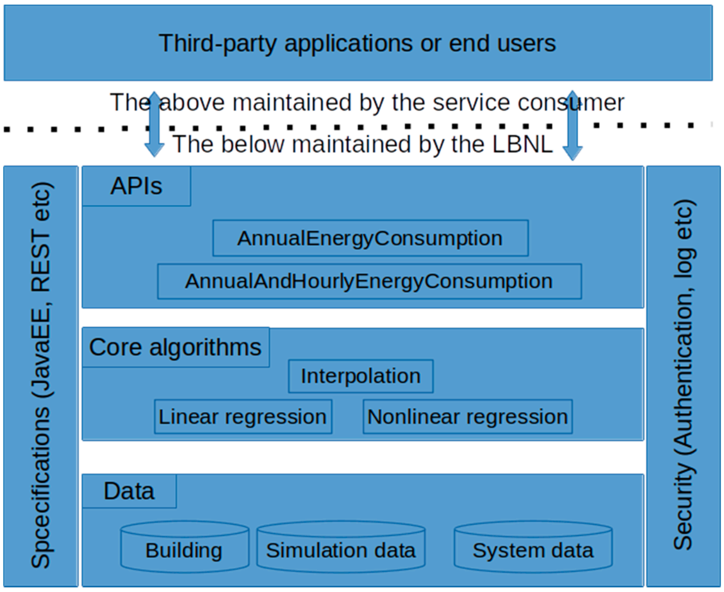

Figure 12. System architecture.

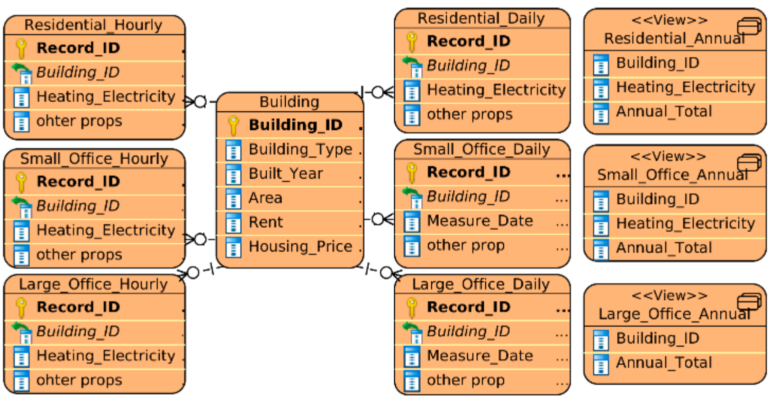

Figure 13. E-R Diagram.

```
{
    status: 200,
    buildingType: "smallOffice",
    description: "OK!",
  - annualEUI: {
        status: 200,
        buildingType: "smallOffice",
        description: "OK!",
        totalEleEUI: 168.91255,
        heatEleEUI: 0.52181,
        coolEleEUI: 20.47633,
        lightEleEUI: 53.6464,
        equipEleEUI: 93.21252,
        fanEleEUI: 0.40941
    },
  + firstDayHourly: […],
  + secondDayHourly: […]
}
```


Figure 14. Output of a RESTful WebService.

The building energy prediction models and the APIs created in this paper can be used to support further third-party urban energy application development. For example, Figure 15 shows an example of an urban building energy prediction platform developed by one of our research partners. Monthly energy consumptions (in EUI) of different building types are color-coded and mapped to individual buildings in a GIS database. Dark red represent a high EUI, while light red represents a lower EUI value. To support HVAC system design and equipment selection, high fidelity hourly EUIs are also provided for typical design days. By clicking any individual buildings from the web-based platform, the annual EUI of the selected building is shown with other building characteristics information, including building height, floor area, year of building, and housing price/rent. If the user toggles the year bar in the bottom, the platform can also visualize energy information in the past and predict future scenarios. This urban-scale 3D platform is currently used by the local government. It provides spatial and temporal building energy assessment and visualization to support design decision makings for city managers and urban planners.

Figure 15. An urban building energy prediction platform developed based on our API [25].

5. Limitations and Future Work

This paper demonstrates the development of residential and office building archetypes using a case study in Wuhan, China. Data-driven regression models were developed based on stochastic simulations. A web-based urban energy platform and an interface were created to support further third-party application development. Future work can be improved based on the following limitations.

A uniform distribution was assumed to generate different design variations for stochastic simulations. The actual distribution was adjusted through post processing to match the distribution of the survey data. In future work, we will apply a Bayesian calibration to consider the probability distribution of key uncertain variables. Due to the limited number of inputs for regression model development, the advantages of more complex non-linear machine learning algorithms, such as support vector machine or gradient boosting, cannot be reflected. In the next step, we will collaborate with our colleagues and partners and collect more available input data to improve our models. In addition, the platform will be fully verified using real-world data from our partners. Furthermore, it is usually straightforward to model building energy consumption for each single building using the traditional physics-based energy simulation methods, but it does not work well for modelling multiple building at community or city level [26–28], hence we are trying to use deep learning to discover the hidden and complex dynamics between multiple buildings so as to make our model more accurate while simulating the city scale energy consumption.

6. Conclusions

Urban-scale building energy consumption data are important for city managers or urban planners. However, an open source national building energy consumption database is not available in China. Instead of an energy consumption survey or measurement, urban scale building energy simulation can play an essential role in sustainable development during the urbanization process. It can enable high resolution analysis to estimate city level energy and track dynamic change. The requirement for citywide dynamic energy consumption information is urgent for city planning and energy policy making. Urban planners and policy makers can use the urban energy simulation platform to support urban-scale spatial and temporal decision-making on energy.

To develop such an urban-scale building energy platform, this paper demonstrates our work on generating a representative building energy consumption database for typical residential building, small office building, and large office building. The reference residential building, small and large office building energy models for Wuhan China were developed in EnergyPlus. The baseline residential reference building was calibrated using China's CRECS2012 building energy survey data to consider different building characteristics and occupants' unique HVAC usage patterns. Stochastic simulations were conducted to generate the numerical building energy consumption database. Three different construction levels were considered to reflect building vintages. Energy consumption distributions were adjusted using Wuhan's housing price and rent data.

Urban-scale building energy simulation requires engineering knowledge and computational resources, which creates a barrier for fast decision-making support. To solve this challenge, the building energy consumption database was further used to develop statistical regression models. To better illustrate our methods and make it easy and friendly to use, we developed a building simulation platform based on JavaEE technologies and standard WebServices. The platform and APIs are expected to provide design support for new constructions as well as for building retrofit. Combined with GIS database, the API can be easily used to develop a 3D urban energy prediction platform. With the support of data visualization, city managers and urban planners can check the spatial and temporal building energy distributions in a city area and assemble fast polices regarding building efficiency and sustainability.

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