Residential Building Archetype and API Development for Urban-scale Building Energy Consumption Platform: A Case Study for Wuhan

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Abstract

Building energy consumption accounts for 30% of the overall energy end use worldwide. Urban scale building energy simulation can play an essential role in urbanization. It allows planners and policy makers to foresee the urbanization through the lens of energy performance. The aim of this research is to develop a cloud-based urban energy simulation platform and an API for Wuhan, China to provide design decision support for urban planning, new constructions as well as for building retrofits. First, baseline residential building energy models are created in EnergyPlus to represent typical building energy consumption in Wuhan. The baseline model simulation results are further validated using survey data from literature. Second, stochastic simulations are conducted to consider different design parameters and occupants' energy usage intensity scenarios, such as building enclosure, lighting power density, equipment power density, HVAC schedule, etc. A building energy consumption database is generated for typical building archetypes. Third, data-driven regression analysis is conducted to output current building energy consumption using simple high-level building information inputs, such as building age and building price/rent. Finally, a web-based urban energy platform and an interface are developed, which support further third-party application development.

Introduction

Building energy consumption accounts for 36% of the global final energy use in 2017 (IEA and UNEP, 2018). This number is even much higher in urban areas (IEA, 2018). Urbanization is one of the critical themes and challenges in the past and this century, especially for some Asian countries, such as China, where city boundaries are expanding with numerous new constructions every year. Rapid urbanization has driven unprecedented economic growth in China, but has also resulted in significant energy consumption (Jiang et al, 2018). Chinese cities are striving to reduce their emissions and to become green and low carbon cities. These cities are searching for strategies to reduce energy consumption and de-carbonize their economies.

To better understand the building energy consumptions in urban areas, it is important to study building energy behavior and to develop an updated urban-scale building energy consumption platform for different buildings types

in China. The basic tools are already developed and ready to use in the U.S., such as the City Building Energy Saver (CityBES), Urban Building Energy Model (UBEM) and Urban-EPC, etc (Chen et al, 2017; Davila et al, 2016; Reinhart and Davila, 2016; Quan et al, 2015).

However, the above case studies are mainly open-loop pure simulation results. It is important to validate the numerical simulation using ground truth building energy survey data. Due to rapid urbanization, China has its own unique demand for urban scale building energy simulation. New constructions account for a large proportion in China. Meanwhile, buildings with different ages exist in the same space, and the time horizon could be several decades. The same type of buildings, if built in different years, the energy consumptions vary a lot. Since an urban-scale platform is rarely found 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 one of our early efforts on building archetype creation for the urban energy simulation platform. Due to page limit, only residential archetype is demonstrated in this paper with the following innovations.

- Build a reference building energy model for residential building type in Wuhan. Currently, there is no well-developed reference building in China.
- Consider energy consumptions of buildings with different year of built.
- Consider unique HVAC schedules and energy usage in Wuhan, China buildings, which is very different compared with those in the U.S. buildings.
- Calibrate the reference building energy models using actual building energy survey data.

With data support from local partners and colleagues, an API is further created for Wuhan to support urban building energy platform development.

Baseline EnergyPlus Model description

The first task is to develop a reference building energy model for Wuhan. The baseline model is created in EnergyPlus. Figure 1 shows the geometry of a typical residential building. It is provided by local building design institute based on survey to represent the most common building configuration in Wuhan. The building has 10 floors and each floor has eight apartments and one

corridor. The total building area is 7,836 m² and the area of each apartment is 88 m².

Local residential building design standard DB42/T 559-2013 is used to define design parameters for building enclosure, HVAC system and building loads, etc (DB42/T 559-2013, 2013). Details of baseline model setting can be found in Appendix Table 2.

This paper considers occupants' actual energy use behavior. Wuhan's hourly weather data is used to simulate annual building energy performance (EnergyPlus, 2018). To create a semi-closed loop for building energy simulation, a calibration of the baseline residential building model is performed using the China Residential Energy Consumption Survey (CRECS) data conducted by Renmin University in 2012.

The CRECS2012 includes residential appliance usage and electricity consumption data from 1450 residential buildings across 26 provinces in China (CRECS, 2012). 218 valid instances from the same climate zone as Wuhan are used to calibrate the baseline residential model. Heating and cooling are provided using ductless mini-split heat pumps. Figure 2 and Figure 3 show the distribution of heating and cooling days in winter and summer, respectively. It can be observed that, compared with cooling, people seem to be more tolerant of heating. Figure 4 shows the daily distribution of heating/cooling hours. We can see that most people use heating/cooling less than 5 hours per day. The heating and cooling schedules as well as the temperature setpoints of the reference building is adjusted according to the survey data.

Figure 1: Geometry of the residential building model.

Figure 2: Distribution of heating days in winter.

Figure 3: Distribution of cooling days in summer.

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

Figure 5: Baseline residential building simulated energy consumption breakdown [kWh/m²].

Figure 6: Distribution of electricity consumption from CRECS survey.

Figure 5 shows the simulated annual energy consumption of the baseline residential building. It can be observed that heating and cooling energy consumptions only account for about 30% of the total electricity consumption. People tends to only use the heat pumps when the weather is too cold or too hot to save electricity bills, which creates important behavioral opportunities for energy savings.

The simulated result total building electricity consumption is 27.8 kWh/m², which matches well with the average electricity consumption from the CRECS survey (see Figure 6). It is noted that the electricity consumption is expected to be 35.3 kWh/m² in the Guideline for Energy Consumption Quota of Civil Buildings in Wuhan (Wuhan Municipal Development and Reform Commission, 2014). When making regional building energy consumption standards, it is important to consider occupants' behavior to reflect actual energy usage pattern.

Stochastic simulations

Based on the calibrated reference residential building model, stochastic simulations are conducted to generate a numerical database for Wuhan's building energy consumption. The building geometry and orientation are fixed to represent the most common configuration in Wuhan. Eight different design parameters, such as *building enclosures, infiltration rate, heating and cooling schedules, lighting power density and equipment power density*, are considered to cover different building ages and design scenarios. To differentiate buildings' year of built, three levels (high, medium and low) of building enclosures are studied by coupling U factors of different parts (external wall, slab, roof and glass).

Besides the different thermal properties of building envelopes, occupancy energy usage pattern is another important factor. According to statistical analysis of the occupants' behavior from the CRECS data, thirteen heating and cooling schedules are covered, ranging from 5% to 95% of the survey data, to reflect different occupants' energy usage levels. For example, 5% means the top 5% of the most efficient energy usage in terms of heating and cooling hours per day and days per year according to the survey data. Due to the limit of computation resources, only typical individual energy end-use profiles are considered. It is assumed that the lighting and plug/equipment loads are coupled with heating/cooling schedules. Other energy usage profiles can be interpolated.

Figure 7 shows an example of the residential building scenario. The combination of residential building baseline model is highlighted in yellow.

Figure 7: 117 parametric combinations of the residential building model.

Stochastic simulations are conducted in EnergyPlus to generate and cover different energy use intensity scenarios. Taking residential building as an example, Figure 8 shows the stochastic simulation results of the annual electricity consumption. It is noted that the electricity consumptions are based on pure stochastic simulations in Figure 7, assuming a uniform distribution of the 117 parametric design scenarios of each building type without any further adjusted weighting factor for each scenario. In reality, there may be less people in the very low or and very high energy consumption percentile. To get a more realistic energy consumption distribution, we collected Wuhan's housing price for residential building (see Figure 9) and adjusted the energy distribution accordingly.

Figure 8: Annual residential building energy consumption distribution of the parametric scenarios.

Figure 9: Wuhan housing price distribution of nearly 19k residential buildings.

Furthermore, a data-driven regression model is conducted to predict building energy consumption. To provide more practical high-level suggestions for urban planners and energy policy makers, the two most common key variables (building's price/rent and year of built) are chosen as model inputs. Various machine learning algorithms are applied to the dataset to compare prediction performance. However, due to very limited number of inputs, more complex algorithms did not show much benefits. Finally, linear regression models as shown in Table 1: Regression functions for residential

building Table 1 are selected, because of its robustness and high prediction accuracy.

Table 1: Regression functions for residential building.

Item	Regression function [kWh/m ²]	R ²
total_ele	$(0.0034 * \text{price} - 29.2658) * (1 + F)$	0.93
heat_ele	$(0.0005 * \text{price} - 3.4929) * (1 + F)$	0.77
cool_ele	$(0.0006 * \text{price} - 5.4794) * (1 + F)$	0.92
Flight_ele	$(0.001 * \text{price} - 9.406) * (1 + F)$	0.95
equip_ele	$(0.0013 * \text{price} - 10.7288) * (1 + F)$	0.95
fan_ele	$(0.00005 * \text{price} - 0.1587) * (1 + F)$	0.89
equip_gas	$(0.0012 * \text{price} - 9.941)$	0.95

Where

$$F = \begin{cases} 0, & \text{if year} = 2010 \\ 0.0245, & \text{if year} = 2000 \\ 0.0603, & \text{if year} = 1990 \end{cases} \quad (1)$$

API and Interface Development

To better illustrate our methods and make it easy and friendly to use, we develop a building simulation platform based on JavaEE technologies (Davila et al, 2016; Cheng and Das, 2014; Quan et al, 2015).

Figure 10 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 and results directly by opening a given service endpoint URL through browser. Our service can also be incorporated into other external systems easily. The second part is the service provider. This is the core part of our platform. It generally includes three main layers: data layer, core algorithms implementation layer, and RESTful Webservice layer. The data layer is responsible to provide enough data to make the platform work securely, such as the building information, system data, and stochastic simulation data.

Figure 11 shows how the simulation data is stored in the database. From the E-R diagram, we can see that hourly building energy consumptions are simulated for the main types of buildings, such as large office, small office and residential, in different scenarios. The core algorithms layer implements the core algorithms to simulate the building energy consumption. This layer mainly includes regression analysis and interpolation algorithms. As mentioned before, our platform will not only be used for our own applications, but it is also expected to support third-party applications. In order to achieve this goal, our platform is designed to be a Service Oriented Architecture (SOA) based program (Newcomer and Lomow, 2005). Specifically, we choose the widely used RESTful Webservice to wrap the core simulation APIs, so that everyone will be able to use our platform by just calling these standard WebServices (Masse, 2011). For instance, people can use the API directly through their browsers by typing into the service endpoint as shown in Figure 12. In addition, third-party applications written in any programming languages are able to incorporate the APIs easily as these APIs are developed using the standard Webservice. We developed a simple interface (see Figure

13) to test and demonstrate how to use the API out of the box service.

Figure 10: System architecture.

Figure 11: 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 12: Output of a RESTful Webservice.

Figure 13: Example interface for testing.

Limitations and Future work

As discussed earlier, there are some limitation in the prediction model development. The main reason is the lack of input data. Using too limited number of inputs, 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 in China and collect more available input data to improve the robustness of our models. In addition, the platform will be fully verified using the real-world data from our partners and/or the third-parties. 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 in community or city level (Jain et al, 2014; Nutkiewicz et al, 2018; Pisello et al, 2012), hence we are trying to use machine learning, specifically deep learning, to learn the hidden and complex dynamics between multiple buildings so as to make our model more accurate while simulating the city scale energy consumption.

Conclusion

Urban scale building energy simulation can play an essential role in urbanization. It allows planners and policy makers to foresee the urbanization through the lens of energy performance. It is also the right time to start this research and study in China, as the basic tools are already developed and ready to use, and the requirement for citywide energy consumption information is urgent for city planning and energy strategy making. To develop such urban-scale building energy platform, this paper demonstrates the process of generating a building energy consumption database for residential and commercial buildings from stochastic simulations. The reference residential and commercial building models for Wuhan China are developed in EnergyPlus. The baseline residential reference building is calibrated using CRECS2012 building energy survey data. Stochastic simulations are conducted to generate a numerical building energy consumption database. Energy consumption density of three different construction levels are considered to reflect buildings constructed in different years. Energy consumption distributions are adjusted using Wuhan's housing price and rent data. This database is further used to predict building energy consumption

through regression analysis to develop statistical regression models. To better illustrate our methods and make it easy and friendly to use for people, we develop a building simulation platform based on JavaEE technologies and standard WebServices, which can be used directly or by third-party applications developed in any language. The platform and APIs are expected to provide design decision support for new constructions as well as for building retrofit. It allows urban planners and policy makers to foresee the urbanization through the lens of energy performance. In the future, a graphical user interface will be developed to provide energy prediction and decision support.

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Appendix

Table 2: Baseline EnergyPlus model settings.

Input parameters	Residential Building
External wall insulation [W/m ² -K]	0.88
Roof insulation [W/m ² -K]	0.447
Ground floor insulation [W/m ² -K]	1.2
External Windows [W/m ² -K]	2.7
Infiltration rate	1
Lighting power density [W/m ²]	Apt: 4.2, Corridor: 1.8
Equipment power density [W/m ²]	Plug load: 2, Kitchen: 5
Occupancy density [m ² /person]	2
HVAC system	Ductless mini-split air conditioner
Heating/Cooling setpoints [°C]	18 / 26
Heating Schedule	19:00-22:00, 1/1-2/14
Cooling Schedule	18:00-22:00, 7/18-8/31

References

- C.C. Davila, C.F. Reinhart, J.L. Bemis. (2016). Modeling Boston : a work flow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets. *Energy*, 117, pp. 237-250
- Cheng, J. C., & Das, M. (2014). A BIM-based web service framework for green building energy simulation and code checking. *Journal of Information Technology in Construction (ITcon)*, 19(8), 150–168.
- China Residential Energy Consumption Survey. (2012). School of Economics, Renmin University, Beijing
- DB42/T 559-2013. (2013). Design standard for residential buildings of low energy consumption.
- EnergyPlus. (2018, 4). Weather Data by Location. Retrieved from EnergyPlus: https://energyplus.net/weather-location/asia_wmo_region_2/CHN//CHN_Hubei.Wuhan.574940_CSWD
- International Energy Agency and the United Nations Environment Programme. (2018). 2018 Global Status Report: towards a zero-emission, efficient and resilient buildings and construction sector.
- U.S. Energy Information Administration (EIA). (2018). Energy Consumption by Sector, https://www.eia.gov/totalenergy/data/monthly/pdf/sec2_3.pdf
- Jain, R. K., Smith, K. M., Culligan, P. J., & Taylor, J. E. (2014). Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Applied Energy*, 123, 168–178.
- Masse, M. (2011). REST API Design Rulebook: Designing Consistent RESTful Web Service Interfaces. O'Reilly Media, Inc.
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. GB 50189-2015. (2015). Design standard for energy efficiency of public buildings. China Architecture and Building Press
- Newcomer, E., & Lomow, G. (2005). Understanding SOA with Web services. Addison-Wesley.
- Nutkiewicz, A., Yang, Z., & Jain, R. K. (2018). Data-driven Urban Energy Simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow. *Applied Energy*, 225, 1176–1189. <https://doi.org/10.1016/j.apenergy.2018.05.023>
- Pisello, A. L., Taylor, J. E., Xu, X., & Cotana, F. (2012). Inter-building effect: Simulating the impact of a network of buildings on the accuracy of building energy performance predictions. *Building and Environment*, 58, 37–45.
- CF Reinhart, CC Davila. (2016). Urban building energy modeling—a review of a nascent field. *Building and Environment*, 97, 196-202
- S.J. Quan, Q. Li, G. Augenbroe, J. Brown, P.P.J. Yang. (2015). Urban Data and Building Energy Modeling: A GIS-based Urban Building Energy Modeling System Using the Urban-EPC Engine, in *Planning Support Systems and Smart Cities*. Springer International Publishing, pp. 447-469
- Wuhan Municipal Development and Reform Commission. (2014). Guideline for Energy Consumption Quota of Civil Buildings in Wuhan-2014 edition.
- Y. Chen, T. Hong, M.A. Piette. (2017). Automatic generation and simulation of urban building energy

models based on city datasets for city-scale building retrofit analysis. *Applied Energy*, 205, pp. 323-335

- Y. Jiang, D. Yan, S. Guo, S. Hu. (2018). *China Building Energy Use 2018*. Beijing: Building Energy Research Center of Tsinghua University.