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A Framework of hybrid building energy forecasting model

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ABSTRACT

There are typically two methods for building energy modeling, which are physical based models and data-driven models. However, the simulation results of physical base energy models often deviate greatly from real cases. While the traditional data-driven energy models are more reliable but only applicable to buildings with historical data record. In this paper, we propose a framework of hybrid building energy models developed based on heterogeneous database which contains integration of building formation, field-tested energy data and simulated energy data. This hybrid energy forecasting model is able to predict building energy in the absence of energy record of the target building. The framework consists of three parts: key variables identification, data integration, heterogeneous database and hybrid energy forecasting model development. A chiller energy forecasting model is developed as a case study to demonstrate the feasibility of this framework. The mean cross testing CV-RMSE and R2 of chiller energy forecasting energy model are 0.17 and 0.86 respectively which are fairly acceptable when historical energy data of target building is not available.

Keywords: building energy forecasting, data integration, Bayesian inference

1. INTRODUCTION

uilding energy modeling (BEM) is increasingly used for building optimization design, construction, operation management and etc. ASHRAE handbook classifies various energy modelling approaches into two type: forward approach and data-driven approach [1]. A BEM program takes as input parameters such as building geometry, construction materials, building usage schedules, mechanical system configuration and control strategies. BEM programs such as Energyplus, DOE-2, eQuest and TRNSYS etc. are most widely used for both research and commercial purpose. However, physics-based BEM programs are often complained because of issues such as complicated geometry modeling process, too many parameters for input, long computation time [2], and large deviation between simulation results and real energy usage [9].

Data-driven modeling uses statistical techniques to capture the mechanism behind the data, without being explicitly programmed [3]. Depending on whether the model considers short-term temperature transients, data-driven models are divided into steady-state model and dynamic model. The steady-state model is appropriate for large granularity (i.e. daily, weekly or monthly) energy estimation. Whereas dynamic model is able to capture the dynamic characteristic when system switching states. The n-P models may be the most well-known steady-state models [4][5]. These are linear regression models which used outdoor dry-bulb temperature or degree-days as the independent regression variable to find building's intrinsic characteristics of energy usage. Data-driven energy prediction models typically use historical data to forecast samples without the needs of large amount computational cost and prior knowledge which are entailed by physical-based models. Hai et al. [6] proposed a novel vector field-based support vector regression method. This method performed better than commonly used ML algorithms through using a vector field to map the original high-dimensional feature space to an optimal feature space. Wang et al. [7] used an ensemble approach, i.e., random forest (RF), for hourly building energy prediction. Feature selection is very important for data-driven model which may influence training data size and model precision. Jin et al. [8] used a set of statistics constructed from raw smart metering data and environment information as the input for building load prediction models. The result showed its effectiveness through real-world data analysis.

However, most existing data-driven models are just applicable for buildings whose historical energy data is available. Machine learning algorithms are trained using historical data to capture the law of energy variation. For new-built buildings or those without energy record, the energy prediction is hard to implement and barely studied. In this paper, we propose a framework of developing hybrid building energy forecasting model which is able to predict building in the absence of energy record data. The hybrid energy forecasting model is developed using data-driven approach. It finds the relationship between key influential variables (which includes building characteristics, weather and occupancy activity) and energy consumption. The key variables concerning building characteristics are inferred using Bayesian inference algorithm. The weather data is collected from local weather station. As the occupancy activity variation follows regular rules of a specific type of building, it is represented by time index and periodicity factor. The model output is time series of building energy consumption integrated by field-tested and simulated energy data which is especially designed for cases when field-tested data is not enough.

2. METHODOLOGY

The framework of proposed hybrid building energy forecasting model is shown in Fig.1. It mainly involves the following three parts:

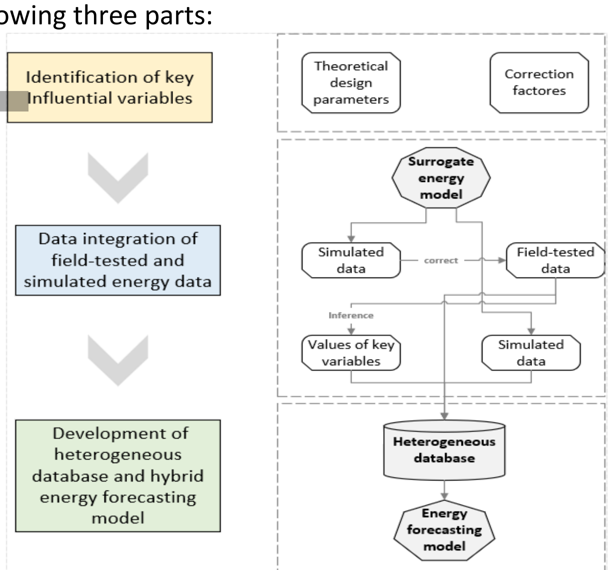


Fig 1. Framework of hybrid building energy model development

(1) Identification of key influential variables. In this part, a minority of variables which have most significant influence on building HVAC energy consumption are identified using sensitivity analysis from all candidate variables. These candidate variables including both theoretical design parameters and correction factors. Correction factors (displayed in Table 1) are the variables which often ignored during design stage but may have major influence on HVAC energy consumption.

(2) Data integration. Field-tested data and model simulation results are both unreliable in some aspect. Field-tested data is easily corrupted by outliers and noise while simulation data is always biased. As is shown in Fig.2, we first correct field-tested data using simulated data. And then the values of key variables are inferred using the corrected data based on Bayesian inference algorithm. The data integration method is applicable for data of various granularity.

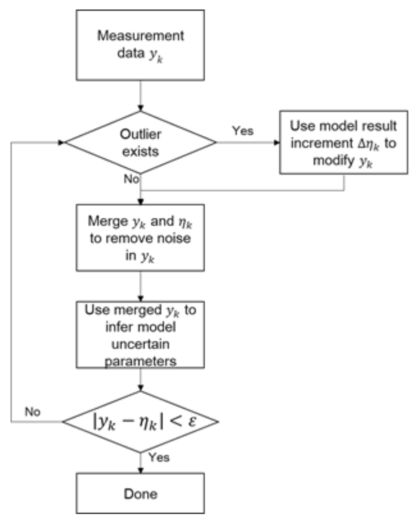


Figure 2 Flowchart of data integration

(3) Establishment of heterogeneous database and hybrid energy models. According to data integrated method mentioned above, we transferred unstructured building information and energy data from different sources (including energy audit reports and energy consumption sub-metering platform) into structured energy data chains. Each data chain contains both key variables and energy consumption of a specific building. These data chains are stored in a database (called heterogeneous energy database in this paper) based on which the hybrid energy forecasting model is trained using key variables as input features and energy data as output.

Table 1 Correction factors of building HVAC energy consumption

Type	Correction factors
Construction deficiency	• Thermal bridge • Air leakage
System deficiency and operational inefficiency	• Large flow and small temperature difference of chilled water system • Coil fouling • Cooling tower fouling • Plant efficiency derogating

3. CASE STUDY

In this paper, the hybrid energy forecasting model for chiller of hotel building is development. Firstly, the key influential variables of chiller energy consumption are identified using two-level sensitivity analysis method. The thermal-load-level key influential variables includes cooling setpoint temperature, infiltration, occupancy density, lighting power density. The system-level ones are water system type, air system type, chiller type, and COP. A surrogate model is developed to produce simulated energy data based on which the field-tested data is corrected. Then the values of key influential variables are inferred using KOH method[10] which is developed based on Bayesian inference algorithm. Part of key variables inference posterior distributions are displayed in Fig.3. The key influential variables together with building basic information and meteorological parameters (including building area, number of layer, lodging ratio, dry temperature and relative humidity) constitute input part of heterogeneous database. Besides, the time index and periodicity factor are employed the occupancy schedule. Time index includes ith day of the month (represented by 1-31), weekday type (represented by 1-31) and ith month of the year (represented by 1-12). The periodicity factor is represent energy use characteristic of each day which can be calculated by the following equation:

$$r_i = \frac{\bar{e}_i}{\bar{e}} \tag{1}$$

Where r_i is the periodicity factor for each weekday, $i = 1, \ldots, 7$ (for Monday, Tuesday,...,Sunday respectively). $\bar{e}_i$ is the mean energy consumption of the ith weekday before the day to be predicted, $\bar{e}$ is the mean energy consumption all types of weekdays. The energy data are collected from buildings from the database. The output of database is composed of chiller energy consumption data of 5 hotel buildings collected by an energy consumption sub-metering platform and energy data of 300 surrogate models simulated by EnergyPlus. At last, the hybrid energy model based on CatBoost algorithm [11] is trained using integration of both field-tested data and simulated data. The field-tested data is given higher training weight so that the model is partial to field-tested data. Due to space limitation, only two cases of hybrid chiller energy model prediction results are displayed in Fig.3. The overall distribution of cross test result of hybrid chiller energy forecasting model is shown in Fig.4. It is obvious that models trained by integrated data are better than those trained only by field-tested data. The reason may be that the simulated data help to enrich the database and improve model performance. With accumulation of measurement data, the training weight of simulated data will be decreased and omitted ultimately.

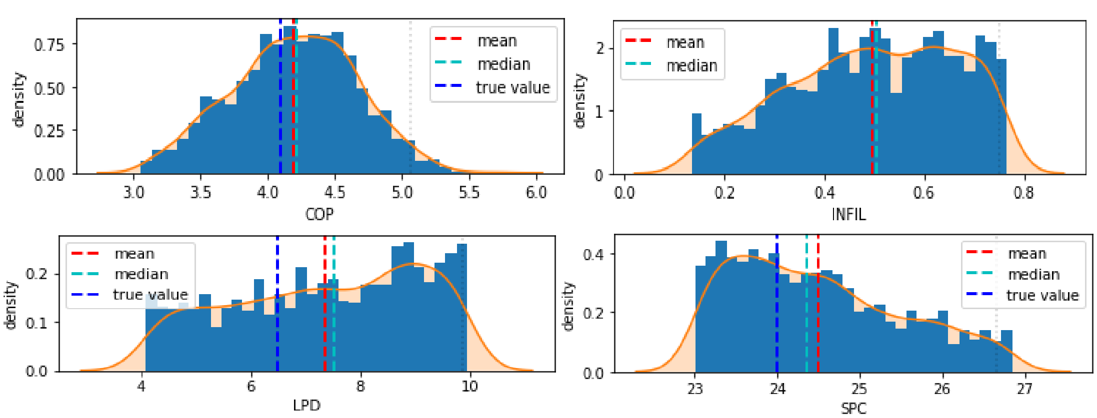
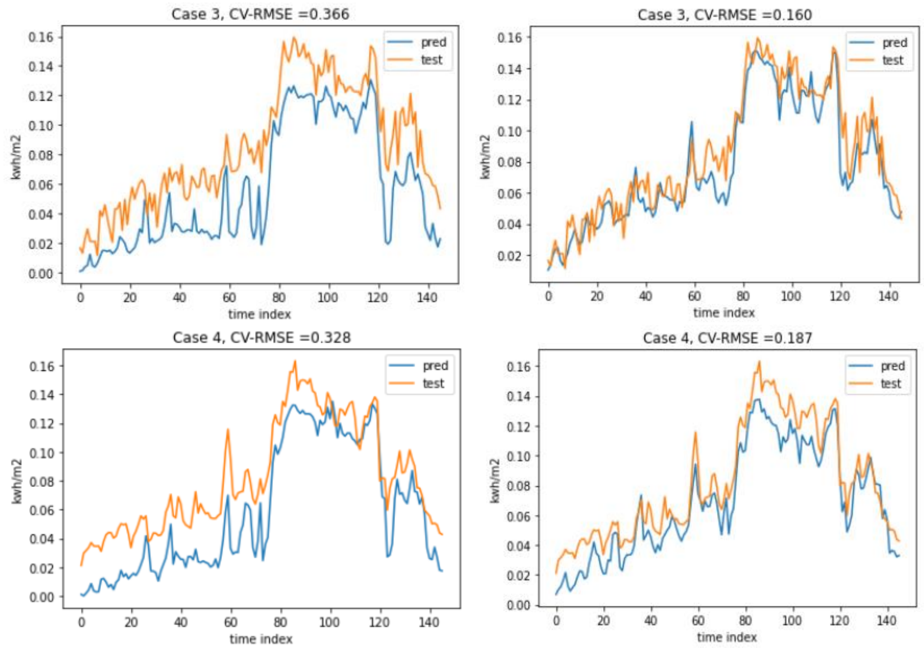


Fig 3. Posterior distribution of key influential variables



(a)Without simulation data (b) With simulation data

Fig 4. Comparison of predicted and test results of hybrid chiller energy model

CONCLUSION

BEM has been widely used to analyze building energy performance. Physical-based models are sophisticated to build and simulation results often deviate from real situation, while data-driven models are only applicable for building with historical data. In this paper, we propose a framework of hybrid energy model which is able to predict energy of buildings when historical energy data is not available. In order to simplify energy model we first identify the key influential variables that dominate building energy variation. The values of key influential variables are inferred based on Bayesian inference algorithm using corrected measurement data as observation. At last, the hybrid energy model is trained with inferred key influential variables as input features and measurement data from various sources and simulated energy data as outputs. The above data are stored in the heterogeneous energy database. A case study of chiller energy prediction model development is conducted to validate this framework. The average CV-RMSE and R2 of this chiller energy prediction model are 0.17 and 0.86 which is fairly acceptable for engineering purpose. We will continue to enrich the database and build prediction models for other plants in the future work. The developed hybrid energy model can be directly used for predicting energy without redeveloping model nor tuning parameter.

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