Beyond Building Energy Simulation Tools

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Abstract. Various energy simulation tools are used to predict energy consumption in buildings at different stages from design to post-occupancy and maintenance. The inaccuracy and insufficiency of inputs used for building energy simulation (BES) often cause a discrepancy between the predicted and actual energy consumption. Inaccurate energy consumption estimations affect the accomplishment of the sustainability goals and reduction of energy consumption and CO2 emissions in buildings. The review of the existing literature suggests that the potential causes of the aforementioned uncertainty in building energy predictions are divided into 2 categories: human error (in design, construction, energy modelling, etc.) and the inaccuracy and insufficiency of inputs in BES. This research proposes the way forward for BES tools to improve their accuracy by enhancing the precision of various energy simulation inputs, integration of real-time data and use of machine learning and other emerging technologies.

1. Introduction: Energy Consumption in Buildings

Buildings are great consumers of energy and producers of GHG emission in the world. In the European Union, US and China, buildings account for nearly 40% of the CO2 emissions and nearly one third of the total energy consumption [1]. The climate change issue has urged governments and scholars around the world to find practical ways to decrease the CO2 emissions in the building sector considerably.

Building energy assessment tools are used to predict the energy consumption at different stages of the building’s lifecycle. The accuracy of building energy predictions rely on the accuracy of the initial inputs provided to the building energy simulation (BES) tool including building properties, weather and location data and occupants’ behaviors [2]. Reliance of energy modelers to energy simulation default assumptions instead of measured data is mainly due to time and cost issues [2].

Uncertainty in building energy prediction is categorized into to groups: human errors and errors caused because of the inaccuracy or insufficiency of inputs in BES tools. Inaccuracy and insufficiency of inputs can be divided into 4 sections: inaccurate weather and location data, building construction and technical details and building model and geometry in the simulation tool and inadequate and unreliable building operation and occupant behavior data.

The weather data used in BES is a historic weather data. However, the climate change and other environmental factors are constantly changing the outside temperature, humidity, rain, etc. Also, the exact characteristics of the building location is often not included in the BES. Other gaps in prediction of energy consumption in buildings are caused because of the gap between design and construction due to deficiency of building material or construction details. Occupants’ behaviours play critical role in energy consumption of buildings [3]. Existing BES tools do not fully incorporate occupants’ behaviours, their relevant inputs are insufficient and their libraries are incomplete. Therefore, there needs to be lots
of studies to fill the existing performance gap. Various methods and techniques (such as monitoring, questionnaire, surveys and advanced sensor technologies) are used by several scholars to predict occupants’ energy-consumption-related behaviours [3, 4]. Machine learning techniques are becoming more and more popular to analyse big data sets available from various existing research on occupants’ energy consumption behaviours considering various influential parameters [5].

2. Building Energy Simulation Tools: The Way Forward

In order to improve the accuracy of building energy consumption simulations, advanced methods of data collection and analysis should be integrated into building energy simulation tools.

2.1. Future Weather Data

For prediction of energy consumption in any building, a yearly set of weather data is required [6]. However, considering the functional age of buildings, climate and consequential changes in the weather should be incorporated into future BES tools [6]. Some scholars investigate different methods (such as Morphing and future climate meteorological year) to predict future weather data [6]. The findings of these studies should be incorporated into future BES tools.

2.2. Smart Systems and Sensors

The application of IoT sensors technology in prediction of real-time energy consumption is mentioned in various studies, however, there are various challenges still remaining such as: the issue of security, data processing and analysis, data coverage and connectivity [7]. Some scholars investigate ways to improve productivity and suitability of sensors for building energy assessment. In a recent study, Frei, Deb [2] proposed an advanced open-source, modular, low-cost wireless sensor network (WSN) for building performance assessment. Integration of real-time data captured by various IoT sensors will create the next generation of BES with better accuracy.

2.3. Interoperability and UX

The lack of user-friendliness of the interface in most of the existing BES tools has been repeatedly questioned by several scholars and practitioners. The main users of BES are energy modelers, researchers, architects and architectural technologists. In comparison to other digital simulations and representations used in the building and construction sector, BES is often perceived as too technical.
Several studies mention human error in running BES as one of the causes of uncertainty in building energy performance analysis. In addition, the interoperability and compatibility of BES tools with other leading tools in the design and construction sectors, particularly BIM tools, still needs to improve. If the building’s geometry is slightly complicated, the interoperability between 3D design modeling tools and BES will drop significantly and the exported gbxml file will not perform accurately in the BES tools.

2.4. Artificial Intelligence: Machine Learning

Energy simulation tools and models with deterministic input control are widely used to analyse and predict buildings energy performance [8]. A high level of complexity and sophistication is introduced with the emergence of IoT and wireless sensing allowing for real time optimization and building automated control [9]. Machine learning is being currently employed to provide more scalable, feasible, and reliable approach to predict energy performance as well as occupant’s behaviour in building. Moreover, with the advancements in smart buildings application machine learning approaches are gaining more interest in order to provide insights and infer knowledge related to the performance and occupants, energy, appliances profiles [10]. This facilitates the building automation and control, anomalous behaviour detection whole promoting energy efficiency.

As evidenced in literature, the level of complexity of the simulation and prediction models varies according to the approaches and considerations. It can be reliant on deterministic values or complicated calculations and algorithms [11]. The machine learning approaches can handle non-linear problems and provide more accuracy in results however they rely on large historical data input that is complex by nature [12]. Although, there is an ongoing advancement in BES tools aiming to provide more reliable and accuracy and a better approach to deal with uncertainty, yet there is still a need to exploration of different concerns for future work:

- Form databases and abundant historical data related to the variables affecting building energy performance which includes occupancy, occupant cantered variables, appliances cantered variables, building cantered variables, loads, and weather related variables [13].
- More consideration for occupant behaviour and the inclusion of occupant specific related parameters should be introduced to the building energy models [14].
- Adaptive and customizable model should be constructed which can serve different building types.
- Privacy preservation of sensitive information and minimizing the privacy impact is a challenge that needs to be explored. Machine learning solution in building are being attractive and more commonly used, it requires data gathering from IoT, devices connectivity via WIFI, and hosting services through the cloud. The cyber security and the communication of these data creates a challenge in terms of smart building privacy. Non-invasive sensing methods and effective communication protocols are hence needed to be explored [15, 16].
- Combining physical inspection methods such as thermal imaging along with computer simulation, allows the analysis of the effect of various factors which aren’t included in the simulation such as thermal bridging, cracks, and overheating. This can be further used to quantify their impact on energy performance and calibrate the models [17].
- Although literature provides evidence that machine learning method could effectively contribute to minimize the energy performance gap and provide more accurate predictions, there is a huge discrepancy in these models in terms of complexity level, use-case building, accuracy of result, scale of historical database, accuracy and level of inputs, and the algorithms and machine learning methods used. A wider look into these models is needed to investigate the strength and weak points and derive lessons learnt for future scenarios. A comprehensive guidance to support future machine learning predictive models construction should be provided to deliver recommendations, suggestions, and solution.

Although machine learning approaches for building energy performance prediction is gaining more maturity, more investigation and advancements are required in terms of methods, accuracy
measurement, input level and quality, scale of database, and scalability and customizability of models in terms of building energy performance prediction.

3. Conclusion

Building energy simulation (BES) tools are constantly evolving to decrease the gap between actual and predicted energy consumption. The potential causes of the performance gap can be categorised into two main groups: human error and lack of sufficient or accurate inputs in BES tools. The way forward for BES tools is to improve interoperability, compatibility and user-friendliness of the tools to improve the UX and decrease energy modellers’ errors. In addition, the incorporation of the BES with advanced future weather data prediction, machine learning methods, smart systems and sensors will improve the accuracy of BES predictions.

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