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Authors
Lin, Yu-Wen
Sun, Ruiji
Schiavon, Stefano
et al.

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Toward Design Automation for Building Models

Yu-Wen Lin[1], Ruiji Sun[2], Stefano Schiavon[2], Costas J. Spanos[1]
[1]Department of Electrical Engineering and Computer Sciences,
University of California, Berkeley, USA
[2]Center for the Built Environment, University of California, Berkeley, USA

Abstract

Building performance simulation is an important tool in building design and operations. Its purpose is to evaluate and optimize energy use, environmental impact, and occupant comfort of buildings. However, the current state of building performance simulation tools is highly fragmented, and the models themselves can be of low quality. In this paper, we present a platform-based design paradigm for building performance models. This approach offers a standardized design flow to ensure that the models are developed in a consistent and systematic way. Additionally, our approach addresses the lack of model performance metrics, allowing for the quantification of model performance. We explore the design flow and model performance quantification with a case study, demonstrating the use of the platform-based design paradigm.

Highlights

- A platform-based design framework is proposed for constructing building models.
- Performance metrics for a two-zone model are developed for model selections.
- The framework is demonstrated through a case study of a testbed.

Introduction

Building performance modeling has numerous advantages in various applications, including design (Machairas et al. (2014)), control (Li and Wen (2014)), demand response (Raza and Khosravi (2015)), fault diagnosis (Kim and Katipamula (2018)), and indoor air quality (Spengler and Chen (2000)). However, models for each application are usually developed independently of each other. For instance, building models constructed during the design phase are frequently not carried over to the operations phase. Additionally, building models designed for fault diagnosis purposes may require a higher level of detail compared to those created for demand response methods. Fault diagnosis models require detailed information about the building's systems and their behavior to identify potential faults accurately. On the other hand, demand response models only need to provide accurate building load predictions to optimize the building's energy usage during peak periods.

Creating a building model for an already constructed building is a complex and challenging task. The level of abstraction is a term that refers to the degree of detail and complexity in a model. It is demonstrated in the electronic design industry, ranging from the system level (less detailed) to the layout level (more detailed) (Weber and Van Noije (2012)). This concept facilitates the creation of a more structured approach to model generation. However, researchers typically build a single model and evaluate its accuracy by comparing it with specific outcomes, such as room temperature or energy consumption often without considering the needed complexity (level of abstraction) would work best for their particular application. The process can be time-consuming and requires significant expertise. To address these challenges, there is a need for an automated, structured, and integrated design method to construct a building model at the required level of abstraction for a specific application.

Building models can be categorized into three different types: white box, black box, and gray box models. White box models, the most common today, involve employing first-principle modeling techniques to capture the dynamics of the physical systems in detail. This type of model has advantages in terms of high fidelity, interpretability, and extrapolation capacity. However, building a physics-based model requires a deep understanding of the system's structures and operations, making it difficult to construct. Additionally, obtaining every required parameter from the physical system can be challenging, increasing the number of uncertainty parameters and making it computationally expensive to solve the systems of equations. Common tools for white box building models include EnergyPlus (Crawley et al. (2001)), TRNSYS (Solar Energy Laboratory (1975)), ESP-r (Strachan et al. (2008)), and Modelica (Fritzson and Engelson (1998)). Solmaz (Solmaz (2019)) provides a comprehensive review of various tools in building simulation, evaluating them based on their features and limitations. Black box models, on the other hand, are easier to construct and can be created based on available sensor data. These models utilize data-driven approaches to create a model based on observed data, without explicitly considering the underlying physical processes. However, black box models are rarely physically interpretable, may suffer from overfitting, may be fragile, and have limited extrapolation capacity. Common data-driven techniques used for predicting the energy performance of a building include artificial neural networks, support vector machines, and Gaussian-based regressions and clustering (Seyedzadeh et al. (2018)). Gray box models find a middle ground between white box and black box models, leveraging available sensor data while also incorporating some level of physics-based understanding. Gray box models aim to preserve some relevant physical properties of the system while also incorporating data-driven techniques to capture system behavior. These models can improve on the limitations of both white box and black box models by offering a better balance between accuracy, interpretability, and computational complexity. Widely employed gray box models of buildings include resistor and capacitor networks (Li et al. (2021)), as well as hybrid models that integrate both physics-based and data-driven techniques (Dong et al. (2016); Lin et al. (2021); Cui et al. (2019)).

Despite the availability of various modeling techniques for building systems, there is a notable gap in comprehensive performance indicators for these models, leading to uncertainty when it comes to selecting the most suitable model for a particular application. Most studies tend to focus solely on accuracy as the primary performance metric, while overlooking essential attributes such as prediction horizon and measurement cost, which are vital aspects of evaluating model performance.

In this paper, we present a platform-based design framework for constructing building models. This framework provides a structured approach to model building at an appropriate level of abstraction for a specific application. Furthermore, we compare three different types of models in terms of multiple performance criteria. These criteria include accuracy, execution time, measurement cost, prediction horizon, and output resolution. By considering these diverse aspects of model performance, we aim to provide a more holistic and comprehensive evaluation of the different modeling techniques used in the field of building systems.

Methodology

Platform-based Design (PBD) approach was developed in the electronic industry as a solution to tackle the rising complexity of hardware-software co-design (Ferrari and Sangiovanni-Vincentelli (1999)). The approach emphasizes the reuse of components across various designs, at varying levels of abstraction, to enable faster and more efficient development of designs. To achieve this, PBD separates function, which characterizes the input-output behavior of the system, from architecture, which refers to the system components, allowing for design space exploration. A mapping process is then employed to match a library of components to the function, enabling the design to move from one level of abstraction to the next. This mapping process can be framed as a multi-objective optimization, where performance metrics are optimized over the design space. The PBD approach involves starting the design process at a high level of abstraction without detailed information and creating an abstract model that limits the design based on a library of components (a platform). This allows for a more modular and structured approach to design, where components can be reused across various designs. The design process itself involves several refinements, from the initial specification to the final implementation, and platforms at different levels of abstraction are utilized throughout these iterations. These platforms serve as a means of organizing and structuring the design process, enabling easier integration of components and a faster turnaround time for design development.

Building performance simulation software can serve as a platform for design, and an example of such software is Modelica (Fritzson and Engelson (1998)) simulation environment. Modelica is an object-oriented language for modeling complex systems. To aid in building modeling, Lawrence Berkeley National Lab (LBNL) developed the Modelica building library (Wetter et al. (2014)) for building modeling that contains white box and gray box models. While the platform has facilitated streamlining the construction of building models, it lacks black box models for design. Although black box models require training data, they can still be developed using previously obtained data from similar buildings and subsequently be updated with measured data. Furthermore, there is still much progress that needs to be made towards achieving the automatic generation of designs. The Functional Mock-up Interface (FMI), a standard for exchanging dynamic simulation models, may be a potential solution for addressing these gaps.

In addition to FMI, other research efforts toward a common platform mostly center around developing control strategies. For example, the Building Optimization Testing Framework (BOPTEST) (Blum et al. (2021)) is a platform that allows users to test various control strategies, while Chen et al. (Chen and Treado (2014)) developed a platform in Matlab for HVAC control analysis. Another approach is the PBD approach, as suggested by Jia et al. (Jia et al. (2018)) for smart building systems, which leverages shared infrastructures for software and hardware components. They demonstrate the effectiveness of their approach through a case study of retrofitting the HVAC system in a smart building, which involved installing sensors and actuators to enhance energy efficiency and improve comfort for occupants.

Our goal is to streamline the process of creating building models for a range of applications. We develop a design flow that is similar to the PBD approach proposed by Jia et al. (2018) but specifically tailored to building model development. Figure 1 illustrates the proposed design flow, which consists of two layers: the functional design layer and the module design layer. Each layer has its own library, which includes the virtual design platform and module platform. The hourglass design in each layer represents a "meet-in-the-middle" strategy, rather than a strictly top-down or bottom-up approach. The design flow begins with a high-level functional specification that outlines the input-output requirements of the model. In the functional design layer, these specifications are mapped to a prototype design using white, gray, and black box models, with the topology provided by the input data model. In the module design layer, the prototype design serves as the specification for further refinement. The final model is constructed by exploring different modules, such as the schedule module, control module, and data analytic module. One key aspect of this design flow is the input data model, which should include the topology of the system to facilitate the design process. Existing data models, such as Brick (Balaji et al. (2016)), can be utilized in this process.

To map a function to components, it is necessary to have performance metrics for building models. Typically, these metrics involve comparing the accuracy of the models by comparing predicted and actual energy consumption or temperature profiles. However, different applications may require different levels of model detail. For example, black box models may suffice for building load forecasting for demand response applications (Chen et al. (2017); Javed et al. (2012)), while more complex models may be necessary for fault diagnosis (Kim and Katipamula (2018)). Therefore, other performance metrics are needed to determine whether a model is appropriate for a specific application. In this paper, we develop performance metrics for a 2-zone model based on both its black box and white box models. Defining these metrics is not a simple task, as it may vary depending on the type and size of the building. For this study, we focus on a small space and plan to develop a more general framework in future work.

Case Studies

In this section, we present a case study involving the construction of three different types of models for a testbed (2 climatic chambers). These models include a white box model, a black box model, and a hybrid box model created at a proper level of abstraction using experimental data. The purpose of creating the white box and black box models is to facilitate the development of performance metrics, while the gray box model serves as a demonstration of the proposed framework.

Experimental Testbed

The measurements used in this study were obtained from a well-instrumented testbed located in Singapore that we designed, build and operate. The testbed has precise control and operation capabilities, and the indoor environment is well-regulated. The testbed room used in the study has dimensions of 25 m^2 and a height of $2.6m$. It is worth noting that the testbed is insulated from the outdoor weather, but an Outdoor Air Emulator (OAE) is available to emulate the outdoor environmental conditions. The measurement period covers May 17th, 2021 to May 31st, 2021. In particular, we develop models of the Heating, Ventilation, and Air-Conditioning (HVAC) system of the physical testbed. The structure of the air system in the testbed is shown in Figure 2.

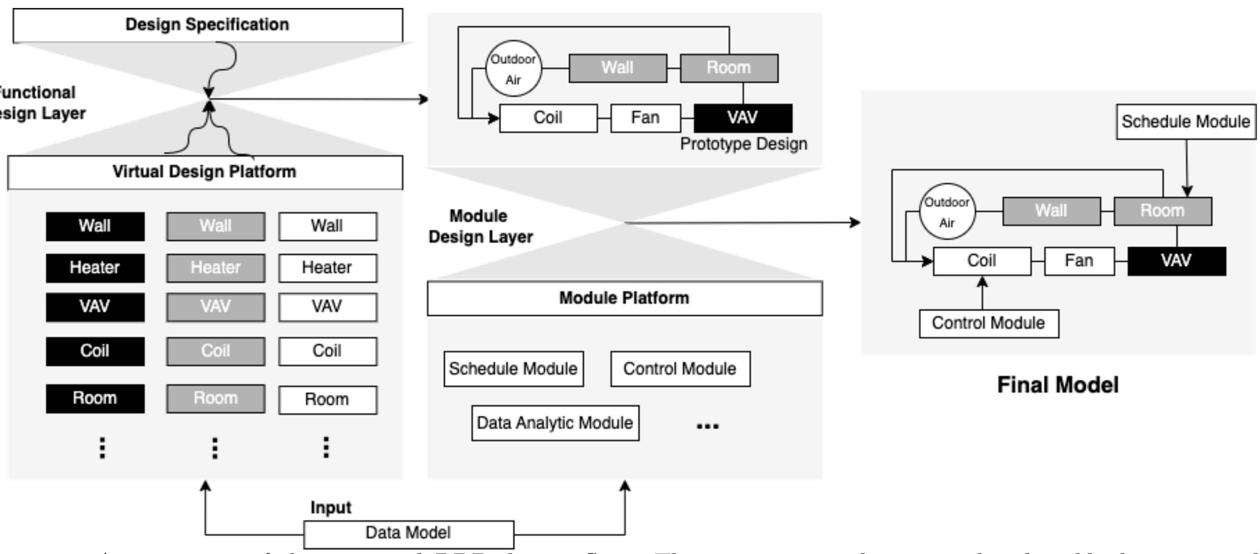


Figure 1: An overview of the proposed PBD design flow. The components that are colored in black, gray, and white in the virtual design platforms represent the black box, gray box, and white box models, respectively.

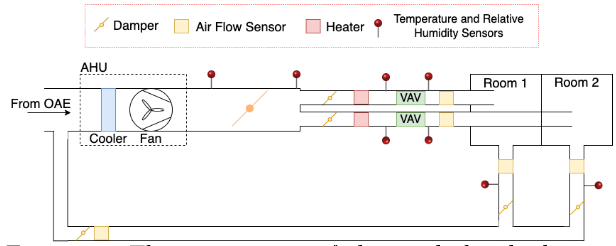


Figure 2: The air system of the testbed, which consists of an Air Handling Unit (AHU) that serves two zones, with a Variable Air Volume (VAV) in each zone. The available measurements in the system are also depicted on the graph.

White Box Model

We used Modelica (Fritzson and Engelson (1998)) for the white box model of the testbed. Modelica is a high-level, object-oriented, and equation-based modeling language used for modeling and simulating complex physical systems. Additionally, Modelica Building Library (Wetter et al. (2014)) developed by Lawrence Berkeley National Laboratory was used to create the model. The constructed model is shown in Figure 3. The result of the cooling load comparison between the measured data and the output of the Modelica is shown in Figure 4a. The Mean Squared Error (MSE) is 0.65 kW.

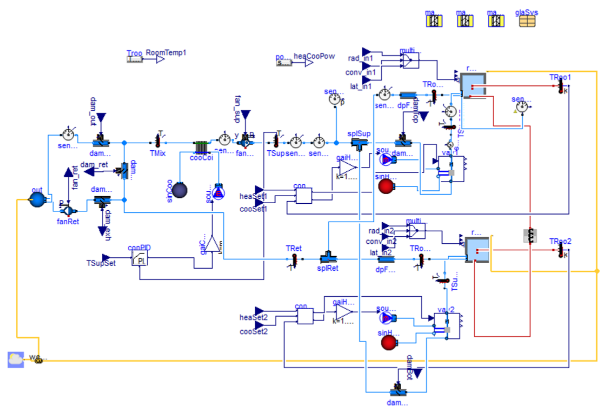


Figure 3: The Modelica Model

Black Box Model

The Random Forest (RF) model has shown promising results in building load forecasting (Dudek (2015); Lahouar and Slama (2015); Fan et al. (2022)). It is an ensemble learning method that combines the predictions of multiple decision trees to produce a more accurate and stable prediction. In a RF model, a large number of decision trees are trained on different subsets of the training data, using random subsets of features at each node to avoid overfitting. During the prediction stage, each decision tree in the forest generates its prediction, and the final output is determined by taking the majority vote of all the individual decision trees.

The cooling load comparison in Figure 4b shows that the black box (RF) model is able to accurately predict cooling load up to a certain time horizon (roughly a day and a half) before the accuracy starts to deteriorate over time. The vertical red dotted line separating the training and validation data indicates that the model was trained on the left side of the line and validated on the right side. The MSE is 0.8 kW. However, the observation that the model's accuracy deteriorates over time suggests that the model may not be capturing all of the underlying dynamics of the system.

Gray Box Model

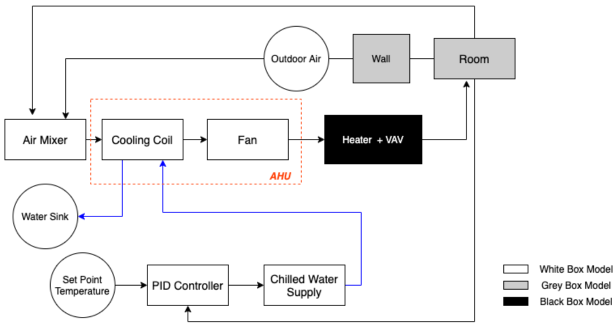


Figure 5: A block diagram that shows the white, gray, and black box model of each component in the air system of the room.

In the gray box modeling approach, developed in Lin et al. (2021), we utilize all three types of modeling, white box, black box, and gray box model to create a model at the level of abstraction of the available sensor data. Figure 5 shows a block diagram of the resulting model. The Air Handling Unit (AHU), which contains a cooling coil and a fan, is modeled as a white box model.

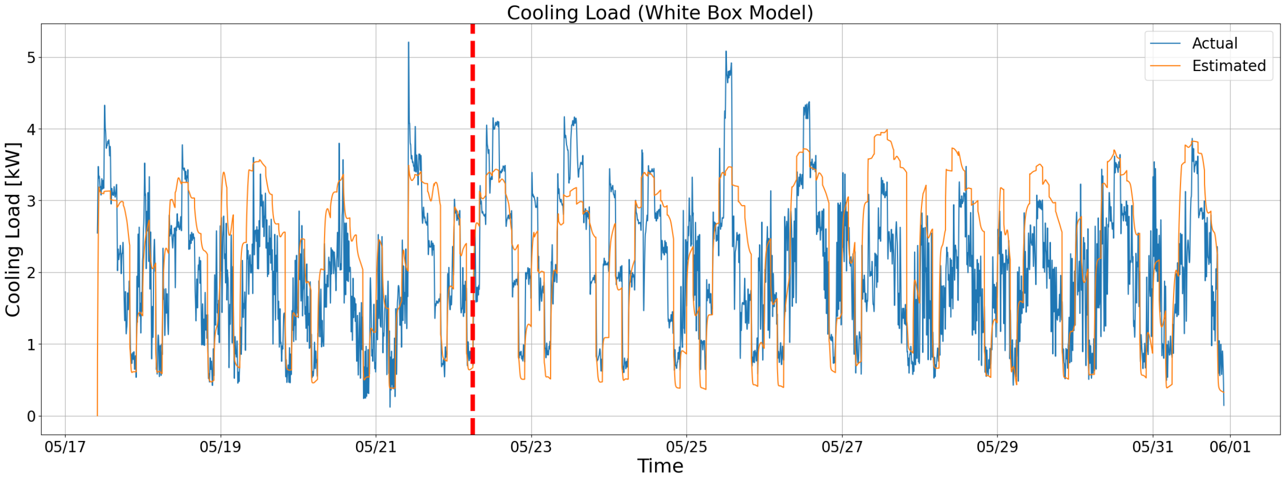
The electric heater and Variable Air Volume (VAV) are modeled together as a black box model. The black box model is created through a two-hidden-layer neural network (Russell and Norvig (2009)) that captures the relationship between the inputs and outputs of the components. ReLu function, which is defined as $relu(x) = \max(x, 0)$, was used to introduce non-linearity in the model. Given the input x, the output $f(x)$ is given by

$$f(x) = relu(w_1 x + b_1) \cdot w_2 + b_2 \qquad (1)$$

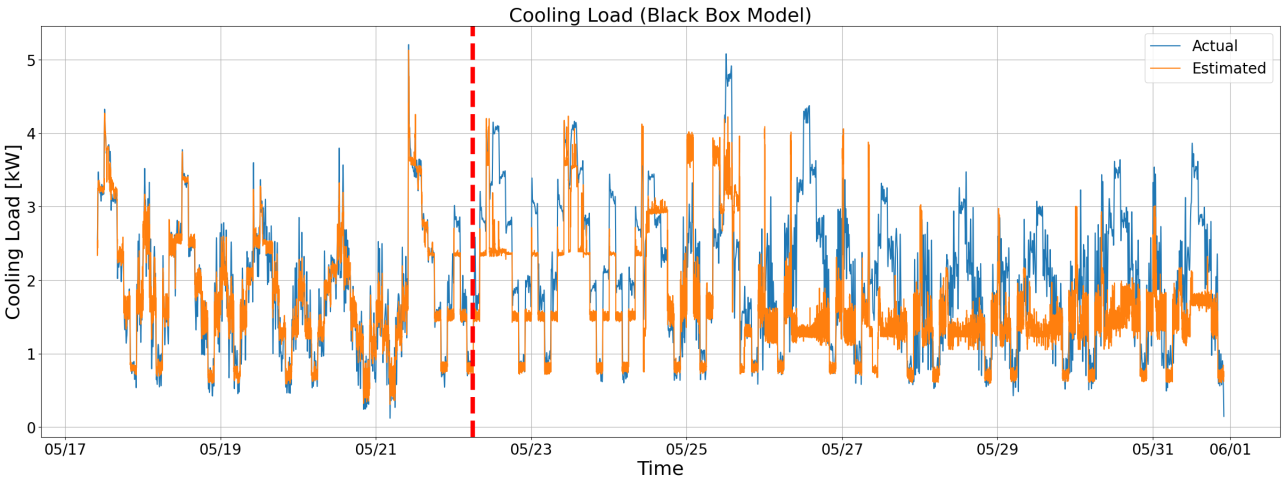
Parameters w_1, b_1, w_2, b_2 are learned during gradient descent. The ML model is trained with a week worth of past data and results in an MSE of 0.1 $°C$.

The properties of the room are modeled as a Resistor-Capacitor (RC) thermal network. A Proportional-Integral-Derivative (PID) feedback controller controlled the chilled water supply flow rate through the cooling coil to indirectly maintain the room set point temperature. The controller is modeled as a white box model. The design choices are made by the information available from the physical testbed to reduce the number of uncertain parameters.

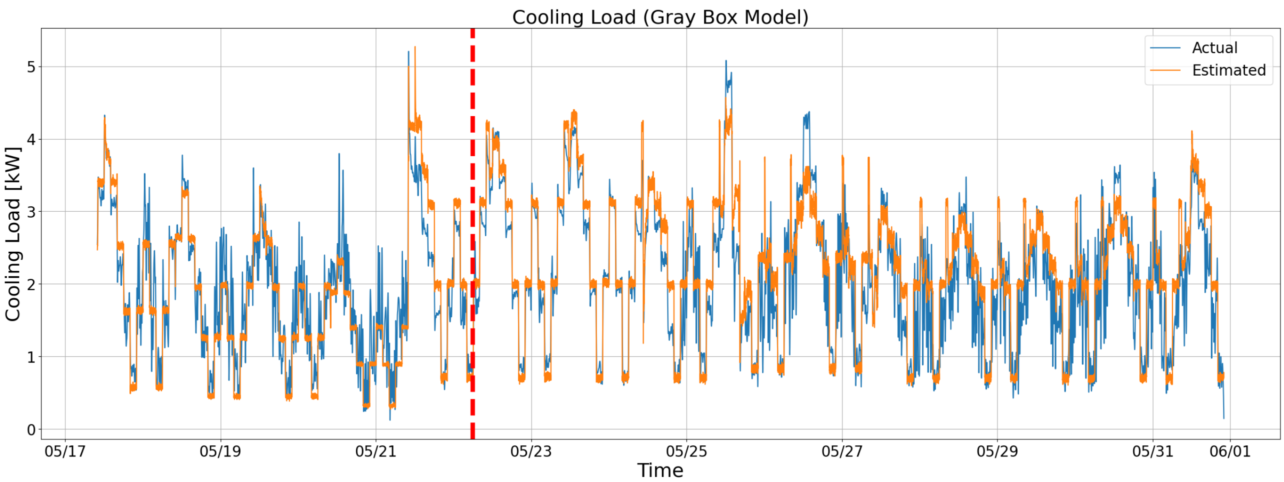
The MSE between the actual and estimated values is $0.2kW$. The gray box model has improved prediction



(a)



(b)



(c)

Figure 4: Comparison of measured and estimated cooling load. The blue line represents the measured cooling load, while the orange line represents the estimated cooling load based on the (a) White Box, (b) Black Box, and (c) Gray Box models. The vertical red dotted line separates the training/calibrating (left) and validation (right) data.

accuracy (0.2 kW vs 0.65 kW for the white box model and 0.8 kW for the black box model) and it also is able to predict the temperature over a long period of the horizon. It combines the strength of both black box and white box models based on the information known in the system.

Model Performance Metrics

Although the case studies have shown that the gray box model provides better prediction results, it's important to note that other factors need to be taken into account to accurately quantify the model's performance. In addition to accuracy, factors such as execution time, measurement cost, prediction horizon, and output resolution are also critical in understanding a model's performance.

As mentioned earlier, accuracy is typically defined as the MSE over a given period of time. Execution time, on the other hand, refers to the amount of time required for the model to predict a certain period of data, such as a week's worth of information. Measurement cost indicates the level of detail required in the input data to build the model, and prediction horizon is the amount of time into the future the model can accurately predict without losing accuracy. Finally, output resolution refers to the number of variables that the model can predict.

To better understand the relative importance of these factors, we provide a table of boundary values specific to a small office space in Table 1. It's important to note that these boundary values may vary depending on the size and complexity of the model being used. Our goal is to emphasize that accuracy is just one of many factors that should be considered when selecting the most suitable model for a given application, and that it's essential to find the most appropriate level of abstraction when evaluating and comparing different models.

Figure 6 presents the ranking of three models based on various attributes. Although their accuracies are comparable, the gray box model achieves the best accuracy, which is crucial considering the unit of cooling load is kW. The execution time of all three models is relatively fast, as the models are small-scale (two-zone model). However, for multi-zone models, the execution time may significantly differ, with the white box model taking the longest time, while the black box model taking the shortest. The black box model requires the least amount of measurements to construct, whereas the white box model requires a higher level of detail about the system to create an accurate model. The gray box model lies between the two in terms of measurement requirements. Both white box and gray box models have a long prediction horizon due to their underlying understanding of physics, while black box models do not benefit from this knowledge. Lastly, the output resolution of the white box model is high due to its complex nature, allowing retrieval of temperature, mass flow rate, or humidity values between each component throughout time. On the other hand, black box models usually only train on a given output or specified outputs. The gray box models lie in between based on the available information.

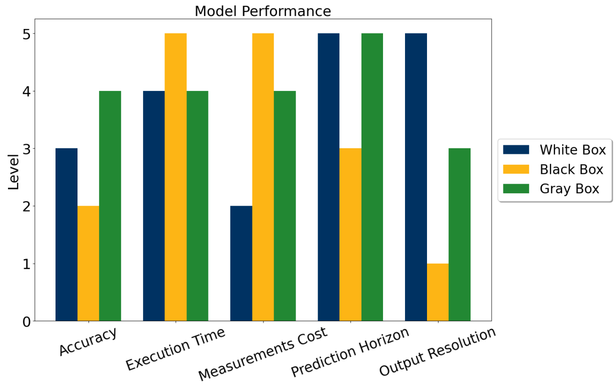


Figure 6: Model performance comparison between white box, black box, and gray box models based on model attributes including accuracy, execution time, measurement cost, prediction horizon, and output resolution.

Different applications often have distinct requirements regarding model performance, and it's essential to consider various attributes to identify the most appropriate model for a specific application. For instance, a highly accurate model that takes a long time to execute may not be suitable for a real-time application, where rapid predictions are critical. Moreover, evaluating different model attributes allows for a more comprehensive understanding of the strengths and weaknesses of various models. It helps to identify trade-offs and enables one to choose the most suitable model based on the specific needs of the application. For example, a model with a lower level of accuracy may be preferred if it executes quickly and has a longer prediction horizon, as it may still provide useful insights for the application. This section serves as a starting point for improving the evaluation of model performance beyond simply comparing model accuracy. The ultimate goal is to establish standardized performance quantification metrics for model selection, allowing researchers to develop the most suitable model for their specific applications.

Discussion

The proposed design flow offers a methodology that aims to streamline the process of generating building models for various applications. However, automating this process fully presents challenges, such as mapping the data model towards the simulation environment and developing a common platform that contains libraries for white box, black box, and gray box models. One of the major challenges is standardization. Standardization is vital to facilitate the reuse of components and improve the efficiency of the de-

Table 1: Model Performance Metric

Model Attribute	Description	1 (Bad)	2	3	4	5 (Good)
Accuracy	MSE [kW]	> 2	< 2	< 1	< 0.7	< 0.1
Execution Time	Time taken for the model to predict a week worth of data [min]	> 10	< 10	< 5	< 3	< 1
Measurement Cost	Measurements requirements to build the model	> 20	< 20	< 15	< 10	< 5
Prediction Horizon	How long can the model predict into the future without losing accuracy [day]	< 0.25	< 1	< 2	< 5	> 5
Output Resolution	The number of variables the model can predict	1	< 3	< 5	< 10	< 15

sign process. The lack of standardization can lead to inefficiencies in modeling and simulation, which can result in suboptimal designs. Thus, there is an urgent need to develop data and library standardization in the building industry.

In this study, we partially realize the PBD framework by developing hybrid models that utilize white box, black box, and gray box models. This approach demonstrates the potential of using these three strategies to create models at an appropriate level of abstraction. However, the current development process is still tedious, as connecting a black box model to a gray or white box model may be difficult due to input-output constraints between components.

Furthermore, the limitations of the case studies are addressed as follows. Measurements under testbed conditions are easier to obtain compared to those taken in real-life buildings because the testbed has a higher density of sensors than a typical building. Further work needs to be done to develop more generalizable models that can be used to model a given physical entity with a smaller and more realistic sensor density. Additionally, the performance metrics are based on small office spaces and may not be suitable for all building sizes and types. Therefore, there is a need to develop more diverse and comprehensive performance metrics that can be applied to a wider range of applications and building types.

Conclusion

In this paper, we developed and compared different types of building models, namely white box, black box, and gray box models, using a testbed in Singapore as the case study. These models are created based on existing data standards, such as Brick, which streamline the model creation process and make it easily transferable to other buildings. We also develop a model performance metric to objectively compare the advantages of different models.

The white box model involves detailed knowledge of the building components, systems, and operations. It requires a high level of input data and incorporates physical laws and equations to simulate the energy performance of the building. The black box model uses empirical data and statistical methods to model the building's energy performance without explicit knowledge of the building's components or systems. It is the simplest and most scalable model, but may sacrifice accuracy. Lastly, the gray box model, on the other hand, uses a combination of detailed and aggregated data, with some components represented in a simplified manner. It enables the creation of models at different levels of abstraction based on the availability of data.

To compare the performance of these models, we develop a set of model performance metrics that takes into account factors such as accuracy, execution time, measurement cost, prediction horizon, and output resolution. By evaluating the models using this metric, designers can objectively assess their strengths and weaknesses, and identify which type of model may be more suitable for their specific applications.

One of the challenges in developing these models is that the process is not entirely automatic. It requires manual efforts to combine various components into a single platform, especially when using a mix of white, black, and gray box approaches. However, the availability of co-simulation platforms that allow different software programs to interact with each other has paved the way for developing an automatic approach to creating building models. These platforms enable the integration of different model types and facilitate the exchange of data and information among them, which can streamline the model creation process. Furthermore, the platform-based approach provides a solid foundation for developing models at different levels of abstraction, which can be tailored to specific applications.

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