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COMPARATIVE ANALYSIS OF WHITE-, GRAY- AND BLACK-BOX MODELS FOR THERMAL SIMULATION OF INDOOR ENVIRONMENT: TEACHING BUILDING CASE STUDY

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ABSTRACT

This study presents a performance comparison between selected white-, gray- and black-box models for indoor temperature prediction in a university building located at the SDU Campus Odense. It was found that the black-box models outperform the gray- and white-box models in most cases, but the accuracy highly depends on the training data in terms of both period and modes of heat transfer covered by the data set. The average mean absolute error for the best performing black-box model was 0.4°C as compared to 1.0°C and 0.7°C for the gray-box and white-box models, respectively. In terms of accuracy, the gray-box models are a reasonable alternative for black-box only in case of short-term predictions, in which their error decreases to around 0.3-0.8°C , depending on the room.

INTRODUCTION

Indoor environment modeling and simulation plays an increasingly important role in advanced HVAC control systems and fault detection and diagnostics (FDD). Simulations can be used to predict future indoor conditions based on the weather forecast and anticipated indoor occupancy patterns. The predictions can be used to optimize the control strategy, e.g. in model predictive control (MPC) systems (Henze 2013). On the other hand, simulations on the historical data can help detect faulty systems by comparing expected results with actual measurements (Turner, Staino, and Basu 2017). In both applications an accurate model of the indoor environment is needed. However, the difficulties related to the development and calibration of building models are often cited as the major obstacle hindering a widespread use of model-based solutions in buildings (Henze 2013).

The modeling approaches can be divided into white-box, gray-box and black-box. The approaches differ in the amount of physical relationships included in the models, with the white-box and black-box being entirely physics-based and data-driven, respectively. The gray-box approach is a mixture of both. The whole-building white-box models are predominant in the design stage, but all three approaches are frequently employed in different building operation applications.

Whole-building white-box models provide detailed insights into the building operation and enable to explore the relationships between the performance of different systems. Due to these features they are used to quantify the effects of faulty systems (Zhang and Hong 2017) or assess thermal renovation strategies and measures (Jradi, Veje, and Jørgensen 2018). White-box models are also used in MPC systems. Although white-box models typically are more difficult to develop than gray- or black-box models, once developed they can be more easily used for other applications like retrofit analysis or FDD (Henze 2013). However, many argue that the calibration of whole-building models is difficult and requires iterations with human-in-the-loop. In consequence, practical application of white-box models in MPC is feasible only for simple buildings (Prívara et al. 2013).

Some of the shortcomings of white-box models are addressed by gray- and black-box approaches. They are usually used to develop more specialized models, e.g. zone models used for temperature prediction (Gunay, O'Brien, and Beausoleil-Morrison 2016), indoor occupancy prediction models (Sangogboye et al. 2017), HVAC subcomponent models (Afram and Janabi-Sharifi 2015b), or overall heating and cooling load prediction models (Ahmad and Chen 2018). The gray- and black-box models are arguably easier to calibrate and more scalable than white-box (Prívara et al. 2013). The scalability addresses one of the commonly cited limitations of MPC, i.e. the significant resources, in terms of both time and expert knowledge, required to provide a reliable control model (Henze 2013).

Some of the reasons the gray-box approach is often preferred over the black-box is the lack of the physical interpretation of the results in the latter (Žáčeková, Váňa, and Cigler 2014). The gray-box models can also provide smooth solutions and be based on twice differentiable equations which make the dynamic optimization more robust, e.g. by using collocation methods (Coninck and Helsen 2016), whereas dynamic optimization in black-box models is usually based on global optimization methods, like genetic algorithms (Reynolds et al. 2018). The gray-box models also have better generalization capabilities when the test data deviates considerably from the training data (Afram and Janabi-Sharifi 2017).

Afram and Janabi-Sharifi (2015a) compared various black-box and gray-box models for HVAC system modeling, including artificial neural networks (ANN), transfer functions (TF), autoregressive exogenous models (ARX),

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