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Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction

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ABSTRACT

Increasing sustainability requirements make evaluating different design options for identifying energy-efficient design ever more important. These requirements demand simulation models that are not only accurate but also fast. Machine Learning (ML) enables effective mimicry of Building Performance Simulation (BPS) while generating results much faster than BPS. Component-Based Machine Learning (CBML) enhances the capabilities of the monolithic ML model. Extending monolithic ML approach, the paper presents deep-learning architectures, component development methods and evaluates their suitability for space exploration in building design. Results indicate that deep learning increases the performance of models over simple artificial neural network models. Methods such as transfer learning and Multi-Task Learning make the component development process more efficient. Testing the deep-learning model on 201 new design cases indicates that its cooling energy prediction (R^2: 0.983) is similar to BPS, while errors for heating energy predictions (R^2: 0.848) are higher than BPS. Higher heating energy prediction error can be resolved by collecting heating data using better design space sampling methods that cover the heating demand distribution effectively. Given that the accuracy of the deep-learning model for heating predictions can be increased, the major advantage of deep-learning models over BPS is their high computation speed. BPS required 1145 s to simulate 201 design cases. Using the deep-learning model, similar results can be obtained in 0.9 s. High computation speed makes deep-learning models suitable for design space exploration.

1. Introduction

Building design is exploratory in nature, whereby architects rely on experiential knowledge [1]. Stringent energy-efficiency requirements call for high-performance building design and operation. Building Performance Simulation (BPS) helps develop buildings that adhere to these demands. Results of BPS are used by designers (architects and engineers) to take appropriate decisions.

The utilisation and generation of BPS results have posed challenges in integrating BPS in the design process. The first challenge is that designers may lack fundamental knowledge of physical phenomena in BPS, making it challenging for them to understand simulation results and take appropriate design decisions [1,2]. Designers also perceive simulations as theoretical. Lack of knowledge and perception tend to make them rely more on rules of thumb and experiential knowledge for decisions if simulations do not provide instantaneous results. Nonetheless, designers are interested in using simulations to improve their designs [1] and their awareness of the design space through simulations allows them to take appropriate design decisions. Simulating multiple design options using BPS can be time consuming. Therefore, it is critical to obtain rapid simulation results in order to avoid the use of conventional knowledge, which may not always be valid, and to explore the entire design space.

The second challenge is that the quality of BPS results depends on the simplification methods applied in the model [3], on the quality of tools and on the skill level of the simulation analyst [4]. The availability of time to perform simulations varies at different design stages. Simulation time affects the complexity of the model used. Developing complex models requires a great deal of time as well as information. Therefore, simple models are used in early design stages and more detailed models as the design stage progresses. Upon design completion, a detailed model is used to validate whether the design complies with energy efficiency requirements. It is therefore important that the simple models are good representations of the detailed model. The ability to simplify a model accurately depends on the technical skills of the analyst. The skill level determines the simplification methods utilised by the analyst to obtain simple BPS. Simplification methods can range from use of building mass to represent building geometry to

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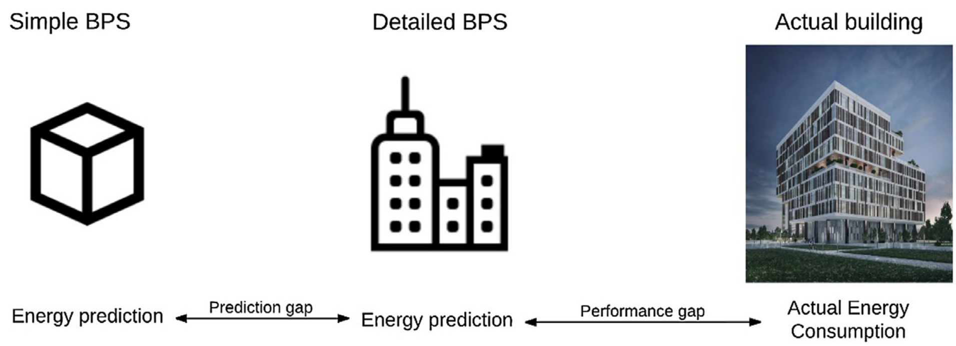

Fig. 1. Illustration of gaps.

seasonal efficiencies for representing Heating Ventilation and Air-Conditioning (HVAC) system. The continuum between simple and detailed models (i.e. simplification method utilised) can induce prediction gap (see Fig. 1) [3]. Prediction gap is the difference between predictions of simple BPS model and detailed BPS model. Definition of prediction gap is comparable to "inter-model variability" defined by Dronkelaar et al. (2016) [5]. High prediction gap compromises the reliability of the decision taken using simple BPS. Wrong decision with simple BPS could result in expensive design changes. Hence, it is important to have models with low- or no prediction gap to ensure the reliability of a design decision.

Furthermore, assumptions (e.g. about occupancy) made in a detailed simulation model are based on the simulation analyst's perceptions of the building [1]. When these perceptions are incorrect, performance gaps are observed [6,7]. The performance gap is defined as the difference between actual energy consumption and design stage energy prediction [6,7]. The key difference between a prediction and a performance gap is that a prediction gap can be reduced by means of correct simplifications, while a performance gap is difficult to reduce during the design stage as it results from uninformed assumptions. Prediction and performance gaps also influence the credibility of BPS, which, in turn, influences designers' perceptions of BPS and its benefits for the design process. Therefore, it is crucial that these gaps be reduced.

The above challenges result in unexplored low-energy design solutions. To limit designers' reliance on conventional methods and change designers' perspective on simulations, analysts must provide reliable and rapid results. Hence, prediction accuracy and computational time[1] to perform simulations play vital roles. Machine Learning (ML) provides the capability of extracting knowledge from data by recognising patterns within them [8]. ML models enable us to capture interactions observed within detailed BPS by means of simple input structures [9]. Is it possible to develop ML models that might complement BPS to overcome these challenges? This paper aims to provide and evaluate deep-learning (a sub-domain of ML) methods that enable the skilled analyst to develop reliable and rapid models for design decisions. To make a case for complementary models (meta/surrogate models) for a BPS model, we start the discussion with basic questions such as 'what is the purpose of a model?' and 'how do ML models fit the grand scheme of sustainable building design?' The discussion is followed by an evaluation of deep-learning methods to highlight their potential for complementing BPS in building design.

2. Background

A model providing the necessary information for design decisions is considered a good model [2]. Generating all of the required information using BPS is possible. Within the constraints of a design program, however, the effort required to obtain necessary information may not be feasible. To address the above challenge, models that emulate and substitute detailed physical simulations are used. In engineering, these models are also referred to as meta-models or surrogate models. ML is an effective way to develop meta/surrogate models. Artificial Neural Network (ANN) is one such model so in this context ML model is synonymous with meta/surrogate model. Meta-models typically have low computation time compared to BPS [10]. Low computation time with sufficient accuracy is ideal for situations where rapid performance feedback is required and also enable the introduction of advanced design optimisation techniques [11,12].

ANN and Support Vector Machines (SVM) are some of the popular ML algorithms used to predict the energy performance of a building [12–20]. Other potential algorithms applied in the context of building energy prediction are decision tree, random forest and multivariate adaptive regression splines [21–23]. These algorithms are applied for rapid design decision energy predictions, for design optimisation based on energy predictions and for operational energy predictions. In all of these applications, ML models provide one response or output and no extra information to support this response. Hence, analysts have to rely on their knowledge to derive possible reasons to support the response in order to make appropriate design recommendations. The authors have proposed the use of a component-based approach to overcome this limitation (i.e. lack of supporting information). The next section contains a brief description of the approach.

Deep learning has outperformed other ML algorithms in domains such as image classification. However, the application of deep-learning algorithms for building energy predictions is limited [24], because the benefits of deep learning are observed in very large datasets, while its performance on smaller datasets is similar to other ML methods. One application of deep learning found in the literature is for short-term cooling energy predictions [25]. Cheng Fan et al. (2017) state that for the developed case and dataset, deep learning did not provide many advantages over traditional methods. However, the features extracted (or representations learned) using deep auto-encoders resulted in significant improvements in prediction performance [25]. Initial research indicated that simple ANN could provide predictions with accuracy similar to deep-learning models [26]. However, initial research only evaluated simple datasets. Data covering broader design parameters can induce more non-linearity and require larger datasets to effectively cover the design space. This paper expands the dataset to evaluate deep-learning architectures and development methods. Finally, implementing models using deep-learning architectures can result in a model size of polynomial nature, while the same representation using a shallow model results in an exponentially sized model [27].

3. Deep learning for the component-based approach

3.1. What is and why use a component-based approach?

ML models are confined to the development dataset's distribution.

[1] Including development and simulation time.