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Achieving Faster Building Energy Model Optimization through Selective Zone Elimination

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ABSTRACT
Optimization in building performance simulation (BPS) has become increasingly important due to the growing need for high-performance building design and operation. Numerous research efforts have been dedicated to decreasing optimization runtime by introducing improved optimization algorithms and advanced sampling techniques. This paper presents a novel model order reduction (MOR) algorithm tailored for speeding up building energy simulation. The algorithm identifies archetype zones simplifying the needless repetition of thermal zones. For an entire optimization process, this MOR method can be repeated recursively to reproduce reduced models. The proposed method can be used to speed up large-scale simulations including optimization, uncertainty analysis and model predictive controls. Preliminary results with parametric simulations show a runtime reduction of about 76% reduction for 15 simulations while still maintaining the predicted total annual energy consumption within a 10% margin. Further research will be conducted to compare the optimization results when applying the proposed MOR algorithm and determine if the reduced model produces the same optimal design. The proposed method may significantly improve the optimization runtime with a minor effect on optimization accuracy, thus increasing the overall usability of BPS optimizations.

KEYWORDS
building performance simulation, EnergyPlus, optimization, model reduction

INTRODUCTION
With the growth of interest in a sustainable built environment, the need for building performance simulation (BPS) has been accelerating (Infiniti Research Limited, 2015). Optimization in BPS has been used to find the optimal building energy performance within a considerable number of design variations. The recent development of generative community and building design have also led to the broader use of optimization in BPS. Furthermore, BPS optimization has also been applied in model predictive control to come up with optimal control strategies. While optimization is a powerful tool, the requirement for computational power and lengthy simulation time have been noted in many previous research, which hinders the practical usage of such technologies.

Reducing computation complexity and speeding up BPS optimization have been investigated by numerous researchers in the past. The following paragraphs will discuss three main approaches to this problem.

The first approach is to improve existing optimization algorithms. Many researchers have looked into improving the efficiency of commonly used optimization algorithms used for BPS (Christensen, Anderson, Horowitz, Courtney, & Spencer, 2006; Hamdy & Sirén, 2016; Nguyen, Reiter, & Rigo, 2014). A faster optimization process decreases the number of simulations needed to obtain the optimal outcome, but it does not reduce the runtime of individual simulations.

Some researchers have also proposed the use of surrogate models. Surrogate models, or meta-models, are statistical models or machine learning models used to imitate BPS outputs based on different parameter changes. Examples of this approach include the use of support vector regression (Eisenhower, O'Neill, Narayanan, Fonoberov, & Mezić, 2012) for BPS optimization. The resulting surrogate models can produce outputs significantly faster than individual simulation runs. The shortcomings of this approach include the requirement of a large simulated dataset, as well as accuracy run-off when the inputs go outside of the trained parameter space. This approach is more reliable when the parameter space remains constrained, which makes it more suitable for model predictive control applications.

Finally, it is possible to reduce BPS model complexity. This approach aims to directly reduce the complexity of the BPS model to cut down simulation time. A mixture of physics-based abstraction and machine learning methods can be used for this purpose. The reduced model can be generated by simplifying the original model, or by building up a template model to approximate the original model. Van Treeck and Rank (2007) demonstrated reduction of building geometry by using graph theory. Georgescu and Mezić (2015) used a Koopman operator to merge similar adjacent zones into a single joint zone. The main disadvantage of this approach is that the reduced model can no longer be transformed back into the original model after the reduction process (Schilders, 2008).

This paper focuses on the building energy simulation (BES) aspect of the BPS. It is an extension of a previously published BPS MOR method called Model-Cluster-Reduce (Shi & O'Brien, 2017). The goal is to achieve faster BES optimization by integrating the MOR method with conventional iterative BES optimization. Unlike surrogate models, this MOR method only requires one simulation to obtain the reduced model. The reduced model is still a standard BPS model capable of accepting parameter changes beyond its trained parameter space. The reduced model and can be opened up for troubleshooting. Throughout this paper, the original BES model is called original model, and the simplified BES model is called reduced model.

METHODOLOGY

In this paper faster optimization is achieved through the reducing the original model from one simulation run, then use it to partially or entirely replace further optimization steps. An overview of this process is shown in Table 1.

For a serial optimization process, multiple optimization steps can be carried out with the reduced model. Then the newly optimized parameters can be validated by a direct comparison between the reduced model and the original model. If the accuracy of the reduced model is confirmed, the optimization path based on the reduced model is accepted, and the optimization process will carry on. For an optimization process using a population, such as evolution algorithm, the reduced model can be used to replace a subpopulation of the models to speed up optimization. After a certain number of optimization steps, the newly updated reduced models need to be validated by the updated original models with the same parameter inputs, similar to the previous serial optimization process.

Table 1. Pseudo code for the proposed optimization procedure

1. Simulate original model
2. Create reduced model through selective zone elimination
3. Simulate reduced model
4. **If** results from the reduced model agrees well with the original model:
5. Optimize reduced model until parameters deviates too much or a certain number of iterations is reached
6. Update original model
7. **Else:**
8. Follow normal optimization procedures

The central philosophy behind this model reduction process is to selectively eliminate redundant thermal zones inside a BPS model and replace them with their archetypes. There are three main steps called model-cluster-reduce for this model reduction process:

The model step captures the characteristics of the original thermal zones by parameterizing a physics-based or statistically-driven model. This step produces a reduced number of parameters from the original model. Parameters estimated from inverse modelling and area normalized heating/cooling profile can be used to represent the zone characteristics. The normalized heating/cooling time series is selected to represent each zone in this paper, and the reduced parameter p is calculated as below:

$$p = \frac{zone\ hourly\ heating/cooling\ load}{zone\ floor\ area}$$

The cluster step uses the parameters obtained from the previous step to group thermal zones automatically using clustering techniques. Then the resulting centres of each clustered group become archetype zones needed for model reduction. Affinity Propagation (AP) is used in this research to form zone clusters and identify archetype zones. AP splits thermal zones into two categories: archetypes and zones belonging to their archetypes. This clustering process is achieved by iterating messages (availability and responsibility) between thermal zones until the similarity distance between the zones and their archetypes are minimized. For details about AP, the original paper by Frey & Dueck (2007). In this application, the similarity distance s is calculated by the Euclidean distance between the thermal zones:

$$s(\beta, \alpha) = -\left\|p_\beta - p_\alpha\right\|^2$$

As its name suggests, s represents how similar zone β is to its archetype zone α. The availability and responsibility are the same from the original AP paper by Frey & Dueck (2007).

The archetype zones are then used to produce the reduced model with a scale factor. All other zones except the archetype zones are removed from the model. The scale factors are calculated from attributes such as floor area and volume. If the boundary condition of the archetype zones' surfaces is not exterior or another archetype zone, it will be converted to adiabatic. In this application the scale factor is calculated from floor area:

$$\lambda_\alpha = \frac{\sum A_{\beta_\alpha}}{A_\alpha}$$

Where λ is the scale factor, A is the zone floor area. More details about the model reduction process can be referred to the original paper by the authors (Shi & O'Brien, 2017).

RESULTS

A calibrated mixed-used building model is created in EnergyPlus (Crawley et al., 2001) and used as a proof of concept demonstration for this paper. The modelled building is located at London, Ontario, Canada. The model contains a total number of 51 zones with a mixture of retail and office space. The reduced model created from the reference design consists of 6 zones in total, resulting in an 86% reduction in computation time for each simulation run on an Intel® i5-7600 processor. For the whole optimization process using the proposed procedure, the total computation time is cut down by about 76%, from 44 minutes to 11.5 minutes.

Figure 1 shows a comparison of the predicted annual consumption from the original model and the reduced model. The difference in total energy consumption is approximately 10%, though with a significant difference in interior lighting. This discrepancy can be explained by the model reduction process being only focused on the heating/cooling response of the thermal zones while overlooking the internal load components. The implications of this will be further commented in the discussion section.

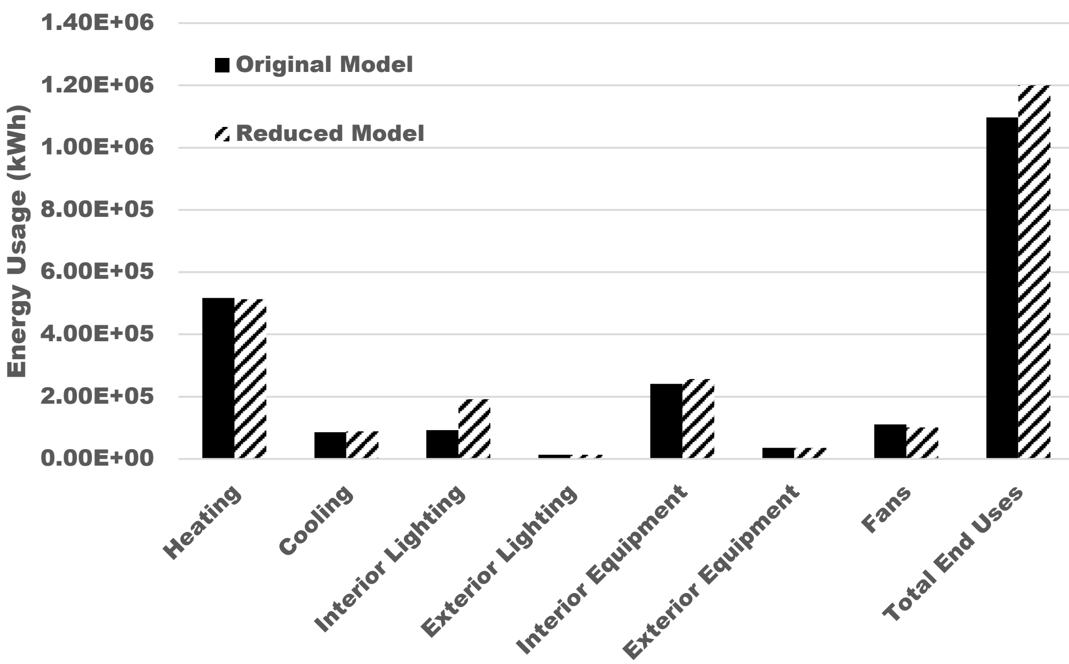

Figure 1. Comparison of the reference models

The reduced model and the original model were further tested in a series of parametric simulations to imitate an optimization process. Insulation levels, infiltration rate and south-facing window type were varied randomly to created 16 samples for each model. The results of these simulation runs are summarized in Figure 2 in the form of energy usage intensity (EUI) in kWh/m^2. EUI of the baseline model is approximately 220 kWh/m^2. As seen in the figure, as the parameter variations become larger and the EUI reduction from the reference model increases, the deviations of the energy savings predicted between the original model and the reduced model becomes larger. To alleviate this deviation inside the reduced model, after the initial ten simulations, the original model was updated with the new parameters, and a new reduced model regenerated. The refreshed reduced model was able to provide closer simulation results to the reduced model, thus making the overall optimization process more reliable.

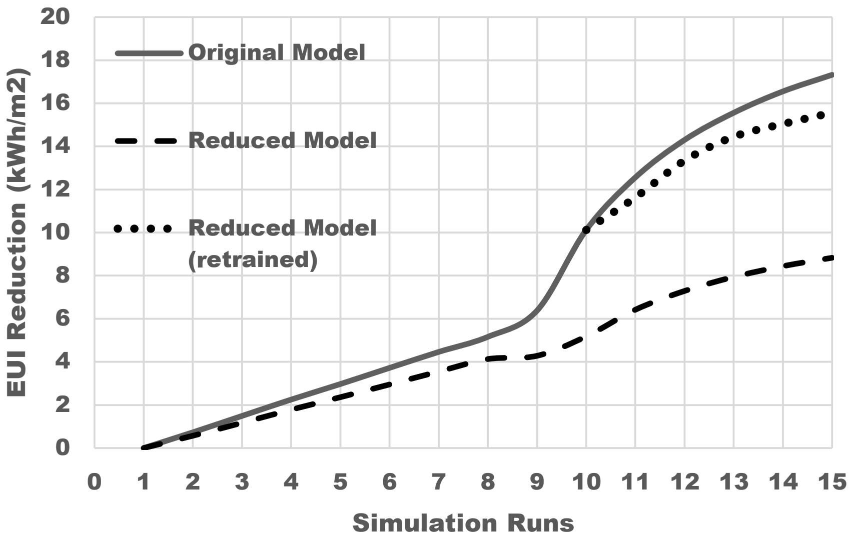

Figure 2. Comparison of the predicted EUI reduction between the original model and the reduced model over 15 simulations

DISCUSSIONS

Overall the proposed model reduction method shows potential to reduce the optimization time of large-scale BES. It also requires much less training data when compared to surrogate models. However, discrepancies in lighting loads were still identified, possibly due to the model reduction process only focused on heating/cooling characteristics. Fortunately, in this case study these loads are less significant than the other components, making the reduced model still reasonably accurate when used for parameter optimization. Other inverse modelling techniques can be tested to determine if this issue could be resolved.

As for the parametric simulation part, the first ten simulation runs performed quite well but the reduced model starts to diverge as its parameters deviate more from the values it was trained from. This mandates an iterative reduced model validation and retraining process inside an actual optimization process. This validation process can be designed to perform intermittently on a determinant number of optimization steps or based on the divergence of parameters from reference values. Even though new reduced models need to be regenerated intermittently, this model reduction process could still significantly reduce the overall simulation time.

Currently, the proposed model reduction process is not yet fully integrated with the existing BES optimization tools; part of the future work would be integrating it as part of a BES optimization package to provide a complete toolkit to the users. More simulation studies are also needed to further validate the proposed model reduction method.

CONCLUSIONS

This paper introduces a novel model order reduction method based on selective zone elimination to achieve faster building energy simulations. This method could significantly reduce the run time of large-scale simulation by providing approximations of best optimization path. Compared to surrogate models based on machine learning methods, this model reduction process still provides a first-principle BES model and requiring fewer simulations to generate training data. The case study used in this paper shows a 76% reduction in total optimization time while still providing reasonable accuracy. The authors are planning to integrate this process with existing BES optimization packages and make it available as an open-source project.

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