Building Energy Model Reduction using Principal Component Analysis and Affinity Propagation Clustering of Thermal Zones

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ABSTRACT

This paper introduces a building energy model reduction method by using one exemplar zone to represent a group of similar thermal zones. The procedure involves using principal component analysis to model and capture the thermal behaviors of the zones, and then use affinity propagation clustering technique to group similar zones together and identify exemplar zones for the clustered groups. A tool has been developed to allow the process to be performed automatically. A case study discussed in this paper demonstrates the proposed method has produced a reduced energy model that allows a magnitude faster simulation than the original model while still maintains the resulting energy consumption estimation within a reasonable range.

KEYWORDS

Model Reduction, Machine Learning, Building Energy Simulation, BIM

INTRODUCTION

Building energy modeling has seen more extensive use and wider adoption by the industry to reduce the energy consumption and greenhouse gas emission during building design and operation periods. Considerable recent research has investigated the topic of using building information modeling (BIM) to automatically generate building energy models. However, BIM models that often contain complex geometries are may not be suitable to be directly used in building energy simulations due to different and sometimes conflicting application requirements. This situation could be further worsened by the growing need to perform building energy simulation iteratively to achieve design optimizations or building control strategy optimizations. Often times the similarities between the thermal zones inside a building and the periodic nature of the indoor and outdoor thermal environment gives the model potential to be simplified.

Some work has been done previously by researchers in an effort to reduce the building energy model complexity using zone approximation and thermal response approximation. Georgescu et al. (2015) introduced a way of applying Koopman operator to capture the thermal behavior of zones at different time scales and using the response similarities to perform model reduction. Goyal et al. (2012) used time-constants to create zone approximations. Van Treeck et al. (2007) demonstrated a way of using graph theory to perform dimension reduction for 3D building models. Some authors (Kim & Braun, 2014, Deng et al., 2010) also focused on developing thermal abstractions or reduced order energy simulation algorithms in order to obtain reduced models.

This paper exploits the possibility of using orthogonal decomposition to capture the first order thermal response of building zones from simulation results, and then use a clustering technique to group similar zones and discover archetypes (exemplary zones). The resulting group formations can be used for HVAC control zone definition during the building design stage, and the exemplary zones can be used to produce reduced model for faster energy simulations. The model reduction process is independent and can be used with the existing available building energy simulation tools such as EnergyPlus and TRNSYS. The proposed method is also validated in EnergyPlus with a detailed energy model of a mixed used academic building. Narayanswamy et al. (2014) demonstrated a similar method as proposed in this paper in the field of building fault detection and diagnostics using Model, Cluster and Compare algorithm.

METHODOLOGY

The proposed energy model reduction method is composed of those major steps as shown in Figure 1: 1)apply principal component analysis (PCA) to capture the thermal characteristics of each thermal zone using simulation results over a training period; 2)pass the variables (loading factors) representing zone's thermal behavior to affinity propagation, a clustering technique to automatically group similar zones together and obtain an exemplar zone representing each group; 3)create the resulting reduced energy model only contains the exemplar zones and their multipliers, and is capable of representing thermal behaviors of the original building.

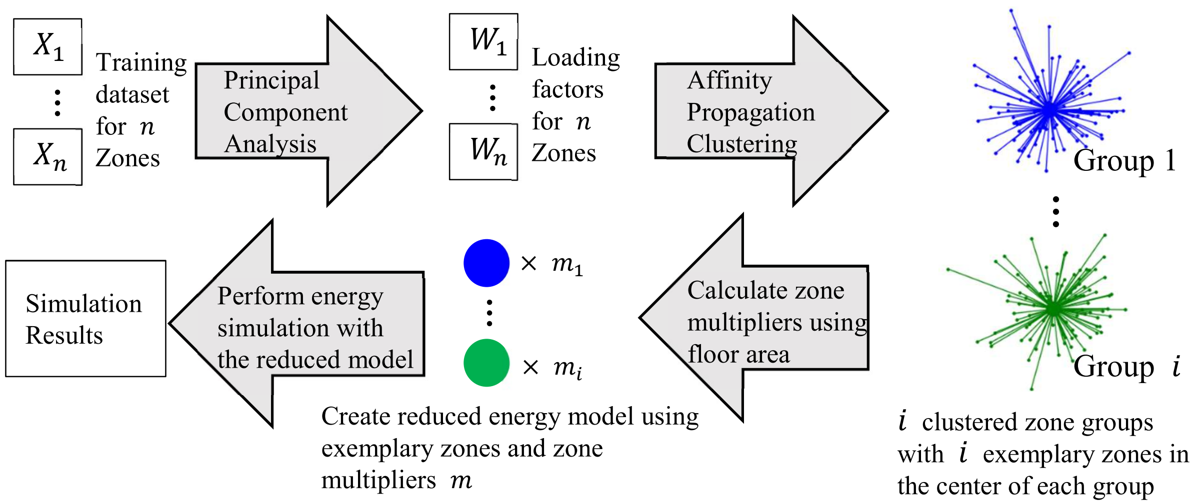

Figure 1. *Procedures of the proposed model reduction method*

Principal Component Analysis (PCA)

Principal component analysis is a powerful statistical procedure which obtains a set of linearly uncorrelated values from a set of possibly correlated variables in a new coordinate system. The order of the new coordinate system is ranked by variance so that higher order coordinate systems represent stronger patterns inside the dataset. The first dimension of the new coordinate system has the greatest variance and is called first principal component, and so on. It is often used in predictive model generation, data dimension reduction and many other applications (Wold et al. 1987).

PCA has also seen some previous applications in building engineering research, mostly in fault detection and diagnostics research. Wang et al. used PCA to perform fault detection and diagnostics in air-handling system (Wang & Xiao, 2004) and its components (Wang & Cui, 2005).

In another study Du et al. used PCA to diagnosis faults in air dampers and VAV terminals (Du et al., 2008).

PCA in this paper, however, is used to model the response of the thermal zones and capture the thermal characteristics of those zones by using a training dataset. Each thermal zone's hourly simulation results that represent its thermal response for a certain training period from the original model is used as dataset X with p variables (columns) and i measurements (rows). In order to make the first principal component most reflective to the zone's thermal behavior, variables chosen for the dataset should comprehensive while still be as independent with each other as possible. Since the chosen variables are likely to take very different magnitudes, min-max scaling is used to preprocess the data. Then the data undergoes the PCA transformation as follows:

$$t_{k(i)} = \ x_{(i)} \cdot w_{(k)} \tag{1}$$

Where $w_{(k)} = (w_1, \dots, w_p)_{(k)}$ is a set of p-dimensional vectors of loading factors that map each row $x_{(i)}$ of X to a new principal component vector $t_{k(i)} = \ (t_1, \dots, t_k)_{(i)}$.
To get the first loading vector $w_{(1)}$, a maximization procedure can be used by:

$$w_{(1)} = \arg\max\{\frac{w^T X^T X w}{w^T w}\} \tag{2}$$

After the first loading vector is obtained, $w_{(1)}$ is then stored for each zone to be passed to the clustering process.

Affinity Propagation Clustering
Clustering, a form of unsupervised classification in the modern statistical learning field, is to group similar objects together based on pattern proximities such as distance, densities or other criteria (Jain, Murty, & Flynn, 1999). It is most commonly used in exploratory data analysis, but in this application, it is intended to group similar building zones together without manually label them.

Affinity propagation (Frey & Dueck, 2007) is used in the current process. It performs clustering by exchanging messages between data points recursively until a high-quality set of exemplars emerges. Instead of producing perfect "virtual" zones as the centers of clustered zone groups, distance-based clustering algorithms such as affinity propagation and k-centers can choose the so-called "exemplars" from the existing zones to be the centers. This feature is preferred since instead of generating new zones from the "virtual" data points which would be too complex, exemplar zones can be directly used in the reduced model. Compared to k-centers algorithm, affinity propagation does not require predefinition of the number of clusters to be classified and is better at handling a large number of clusters and less prone to random initialization issues (Frey & Dueck, 2007). Given the advantages mentioned above, affinity propagation was selected in this paper.

Affinity propagation works by treating the first loading vectors ($w_{(1)}$) of each zone from the PCA analysis as node in a network, and then recursively finding the best set of exemplar zones so that the network similarity $s(i, k)$ is minimized. In this paper Euclidean distance, or negative squared error, is used to calculate the similarity:

$$s(i,k) = -\left\| w_{(1),i} - w_{(1),k} \right\|^2 \quad (3)$$

where i is the zone index and k is the exemplar index.
To determine the number of clusters, $s(k,k)$, or so-called "preferences", need to be defined for each zone. Zones with higher preference are more likely to be chosen as exemplars. In this application, since all zones are likely to be exemplars, the preferences are set automatically to be the median of input similarities $s(k,k)$, which means the final cluster formation is better than each zone forming its own group.

Two kinds of messages are passed between zones recursively to compete and determine whether a data point should be an exemplar (responsibility) or belong to another exemplar (availability). The following equations define those two kinds of messages:

$$responsibility\text{: } r(i,k) \leftarrow s(i,k) - \max_{k' s.t. k' \neq k} \{a(i,k') + s(i,k')\} \quad (4)$$

$$availability\text{: } a(i,k) \leftarrow \min\{0, r(k,k) + \textstyle\sum_{i' s.t. i' \notin \{i,k\}} \max\{0, r(i',k)\}\} \quad (5)$$

To better illustrate those two kinds of messages: responsibility $r(i,k)$ indicates the accumulative evidence supporting how well-suited zone k is the exemplar of zone i. Whereas availability $a(i,k)$ reflects the accumulated evidence showing how well-suited zone i belongs to the exemplar zone k.

During the first iteration, the availabilities are set to zero. For $k = i$, $r(k,k)$ is set to be the input preference $s(k,k)$. Unlike availability $a(i,k)$, self-availability $a(k,k)$ is formulated as the following to avoid the influence of strong positive responsibilities, both self-responsibility $r(k,k)$ and self-availability $a(i,k)$ reflect the accumulative evidence that zone k is an exemplar.

$$a(k,k) \leftarrow \textstyle\sum_{i' s.t. i' \neq k} \max\{0, r(i',k)\} \quad (6)$$

A damping factor, λ is used to avoid potential oscillations. Each message is λ times its previous value plus $1-\lambda$ times the current value. In this application, the default damping factor of 0.5 is used. During each iteration, the exemplars are determined so that $a(i,k) + r(i,k)$ are maximized. The algorithm is terminated and results produced when more than 15 iterations are achieved without changes in the cluster structure. After all thermal zones are clustered, only the exemplar zones are kept in the original building model, and zone multiplier is used to adjust for the total floor area of each group.

EXPERIMENTAL SETUP

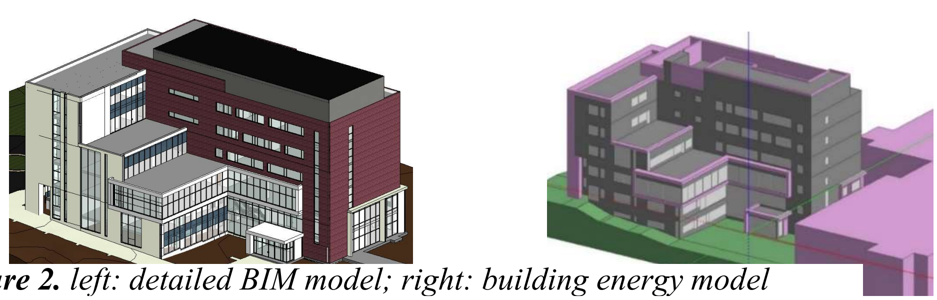

Figure 2. *left: detailed BIM model; right: building energy model*

An experiment was carried out to evaluate the effectiveness of the proposed methodology and demonstrate its usage as a proof of concept. A 7-story academic building was selected for this study. Canal building is located at Carleton University, Ottawa Ontario, Canada and has a mixture of private offices, open offices, conference rooms, classrooms, labs, retails, common areas and other utility rooms. This mixed usage nature challenges the proposed method's ability to identify distinct thermal characteristics of different zone types and orientations. A complex and calibrated Building Information Modeling (BIM) model was created in a previous study (Figure 2) (Shi et al., 2015). The converted energy model contains 264 thermal zones and more than 3800 surfaces, making it too complex for fast retrofit parametric analysis and model predictive control applications. The building is conditioned by a VAV system in the original energy model. Based on past experience, the smallest number of variables that may best represent the thermal response are chosen as in Table 1.

Table 1. *Collected zone variables*

Included Variables	Type
Outdoor dry bulb temperature	Environment
Solar azimuth angle	Environment
Solar altitude angle	Environment
Direct solar insolation	Environment
Diffused horizontal solar insulation	Environment
Zone mean air temperature	Zone
Zone mean air temperature change	Zone
Zone heating/cooling rate	Zone

EnergyPlus was selected as the energy simulation tool. A simulation period of one month was used to generate the training data. In order to produce the reduced model in EnergyPlus, only exemplar zones with multiplies and their related entities are kept, and all interior surfaces of the exemplary zones are changed to adiabatic boundary conditions.

To automate the process, a tool was written in Python to read the .idf file (EnergyPlus input file), perform training simulation, read the .eso output file, then perform the model reduction procedure and generate the reduced .idf file accordingly. A Python machine learning package scikit-learn (Pedregosa et al., 2012) was used to perform principal component analysis and affinity propagation clustering. Another Python package, Eppy, was used to handle Energyplus interfacing, training .eso data parsing and .idf file manipulations. The simulations were performed on a 1st generation i-7 CPU with a clock speed of 2.67GHz.

RESULTS AND DISCUSSION

Table ***2*** shows the model and simulation comparison between the original model and the reduced model in EnergyPlus, and Figure 2 shows an example floor plan of the original thermal zones clustered into different groups coded by different color. The number of thermal zones and building surfaces has been reduced by 94.7% and 95.9%, respectively. The simulation time has also been reduced by 96.6%, allowing for significant computation reduction. The new reduced model enables a more realistic potential usage of the whole building simulation for model predictive control and fast parametric analysis.

Table 2. *Model and simulation time comparison*

	Original Model	***Reduced Model***
Thermal Zones	264	14
Surfaces	3,878	158
Simulation Time (1-year)	47’50”	2’12”
Computation Time Reduction (1-year)	/	95.6%

Figure 3*. Example floor plan of zone groups indicated by different colors, zones from multiple floors may belong to the same group due to similar thermal behaviors*

Table 3 compares the simulation results between the original model and reduced model. The differences in the energy consumption between the original model and the reduced model are relatively small considering the magnitude of model complexity reduction from the original model. There is a large discrepancy for the fan energy consumption, though and may be caused by the fact that only floor area is used to calculate the zone multiplier, not zone volume. The difference between the equipment loads is also quite larger, but this can be caused by the fact that another casual heat gain source, lighting load, is much higher than the equipment loads, so the characteristics of equipment usage are not well represented by the loading factors.

Overall the results indicate that the proposed model reduction method has potential for wider adoptions, but further tests with more building models are required to test the method's robustness. However, volume is not considered in this model reduction and may lead to issues for specialized thermal zones which contains theatres and lecture halls. Furthermore, whether the method tends to overestimate energy consumption need to be analyzed as well.

Parametric simulation results between the original model and reduced model need to be compared so that the capability of the proposed method as a way of performing reduced parametric analysis can be further validated.

Table 3. *Simulation results*

	Original Model	***Reduced Model***	***Difference***
Natural Gas (kWh)			
Heating	1,582,828	1,482,281	-6.78%
Electricity (kWh)			
Cooling	108,333	117,904	8.83%
Lighting	121,749	120,483	-1.04%
Equipment	39,445	35,424	-10.19%
Fans	95,621	109,448	14.46%
Pumps	77,850	75,278	-3.30%
Cooling Tower	2,833	3,083	8.82%
Total Electricity	445,831	460,620	3.54%
Water (m^3)			
Cooling Tower	1,526	1,602	4.98%

Principal component analysis used in this paper does not capture the nonlinearity of the zones' thermal responses. The Koopman operator used by (Georgescu & Mezić, 2015) is able to capture all the nonlinearity of a dynamical system and is worth further investigation and comparison.

As of now the proposed clustering process only captures the thermal behavior of the building zones. Even though thermal response gives an aggregation of the other energy loads such as equipment load and lighting load inside a room, theoretically it would be more robust for the method to include other zone behaviors such as equipment usage patterns and lighting usage patterns.

CONCLUSIONS

This paper presented a methodology to perform building energy model reduction by applying principal component analysis to capture thermal behavior of the zones and then use affinity propagation to group similar zones together. A case study was also performed to demonstrate the effectiveness of the proposed method. Overall this novel method produced relatively similar energy consumption results while reducing the computation time by more than 95% in Energyplus. A tool was developed during this research and can be readily used with existing building energy simulation tools as an add-on, and has potential implications in building design simulations, HVAC control zoning definitions and building model predictive controls. In addition to the content in this paper, further study is needed to further improve its performance and test the algorithm's robustness.

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REFERENCES

Deng, K., Barooah, P., Mehta, P. G., & Meyn, S. P. (2010). Building Thermal Model Reduction via Aggregation of States. In *American Control Conference (ACC)* (pp. 5118–5123).

Du, Z., Jin, X., & Yang, X. (2008). A robot fault diagnostic tool for flow rate sensors in air dampers and VAV terminals. *Energy and Buildings*, *41*, 279–286.

Frey, B. J., & Dueck, D. (2007). Clustering by passing messages between data points. *Science*, *315*(5864), 972–977.

Georgescu, M., & Mezić, I. (2015). Building energy modeling: A systematic approach to zoning and model reduction using Koopman Mode Analysis. *Energy and Buildings*, *86*, 794–802.

Goyal, S., & Barooah, P. (2012). A method for model-reduction of non-linear thermal dynamics of multi-zone buildings. *Energy and Buildings*, *47*, 332–340.

Jain, a. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: a review. *ACM Computing Surveys*, *31*(3), 264–323.

Kim, D., & Braun, J. E. (2014). A general approach for generating reduced-order models for large multi-zone buildings. *Journal of Building Performance Simulation*, *1493*(November), 1–14.

Narayanaswamy, B., Balaji, B., Gupta, R., & Agarwal, Y. (2014). Data driven investigation of faults in HVAC systems with model, cluster and compare (MCC). *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings - BuildSys '14*, (Mcc), 50–59.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Duchesnay, É. (2012). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Shi, Z., Abdelalim, A., O'Brien, W., Attar, R., Akiki, P., Graham, K., … Khan, A. (2015). Digital Campus Innovation Project : Integration of Building Information Modelling with Building Performance Simulation and Building Diagnostics. In *SimAUD 2015*.

van Treeck, C., & Rank, E. (2007). Dimensional reduction of 3D building models using graph theory and its application in building energy simulation. *Engineering with Computers*, *23*(2), 109–122.

Wang, S., & Cui, J. (2005). Sensor-fault detection, diagnosis and estimation for centrifugal chiller systems using principal-component analysis method. *Applied Energy*, *82*(3), 197–213.

Wang, S., & Xiao, F. (2004). AHU sensor fault diagnosis using principal component analysis method. *Energy and Buildings*, *36*(2), 147–160.

Wold, S., Esbensen, K., & Geladi, P. (1987). Principal component analysis. *Chemometrics and Intelligent Laboratory Systems*, *2*(1–3), 37–52.