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Investigation of Energy Modelling Methods of Multiple Fidelities: A Case Study

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ABSTRACT
Building energy modelling has become an integral part of building design due to energy consumption concerns in sustainable buildings. As such, energy modelling methods have evolved to the point of including higher-order physics, complex interconnected components and sub-systems. Despite advances in computer capacity, the cost of generating and running complex energy simulations makes it impractical to rely exclusively on such higher fidelity energy modelling for exploring a large set of design alternatives. This challenge of exploring a large set of alternatives efficiently might be overcome by using surrogate models to generalize across the large design space from an evaluation of a sparse subset of design alternatives by higher fidelity energy modelling or by using a set of multi-fidelity models in combination to efficiently evaluate the design space. Given there exists a variety of building energy modelling methods for energy estimation, multi-fidelity modelling could be a promising approach for broad exploration of design spaces to identify sustainable building designs. Hence, this study investigates energy estimates from three energy modelling methods (modified bin, degree day, EnergyPlus) over a range of design variables and climatic regions. The goal is to better understand how their outputs compare to each other and whether they might be suitable for a multi-fidelity modelling approach. The results show that modified bin and degree day methods yield energy use estimates of similar magnitude to each other but are typically higher than results from EnergyPlus. The differences in the results were traced, as expected, to the heating and cooling end-uses, and specifically to the heat gain and heat loss through opaque (i.e., walls, floors, roofs) and window surfaces. The observed trends show the potential for these methods to be used for multi-fidelity modelling, thereby allowing building designers to broadly consider and compare more design alternatives earlier in the design process.

KEYWORDS
Building energy modelling, multi-fidelity, modified bin, degree day, dynamic simulation

INTRODUCTION
Advancements in building energy modelling methods have helped building designers to gain more insights into the energy use of prospective building designs (Lam et al., 2014). However, the increased complexity of these methods has often hindered their use to broadly explore and compare design alternatives early in the design process. In various fields of engineering design, some of the approaches to resolving this issue have included fitting a surrogate model to data from high fidelity (i.e. expensive) model evaluation of a sparse subset of the design space (for example Forrester, 2007, Unal et al., 1996), or through multi-fidelity modelling approaches (Jin, 2001; Simpson et al., 2001). One method in particular, uses a set of multi-fidelity models in sequence to evaluate the design space whereby low-fidelity models are used to remove non-optimal designs prior to evaluation by higher fidelity models (Miller et al.,2017). In the building

design field, prior efforts have been taken to review and categorize load estimation methods such as ASHRAE's Cooling Load Transfer Function (CLTD), Radiant Time Series (RTS), Transfer function methods and Heat Balance Method (HBM) based on their increasing levels of complexity and accuracy (ASHRAE 2009). However, such efforts were focused on comparing the differences of the underlying calculation procedures and to our knowledge, there is a limited number of studies comparing the outputs of the various energy modelling methods in the context of a *multi-fidelity modelling approach*. Given that the building design community possesses many energy modelling methods ranging from simple spreadsheets utilizing temperature-bin methods to simulation-based energy modelling tools such as EnergyPlus (Mao et al., 2013; Crawley et al., 2008), a multi-fidelity modelling approach could be a viable solution to the issue of exploring large sets of design alternatives. Here we investigate energy estimates from three candidate energy modelling methods to assess how they compare to each other, if there are any general trends across the methods, and whether they may be suitable for a multi-fidelity modelling framework.

METHODS

Selection of energy modelling methods

Annual building energy use can be estimated using three types of energy modelling methods: (1) *forward or classical methods* - based on a building model and engineering calculation methods (ASHRAE, 2009); (2) *data-driven methods* - based on building system parameters from actual measured data (ASHRAE, 2009); and (3) *simulations* - that estimate energy requirements using differential equation solvers for transient simulations and time-stepping weather data (Mao et al., 2013). Forward methods include the thermal response factor method (Mitalas & Stephenson, 1967), weighting factor method (ASHRAE, 1981) and the heat balance method (Buchberg,1958; Kusuda,1999) for annual heating/cooling load estimation and degree day method, equivalent full load hour method, bin method (Ayres and Stamper, 1995) and modified bin method (Knebel, 1983) for annual energy use calculation. Simulation methods used in the United States typically include whole building dynamic simulation tools such as DOE-2, eQuest, EnergyPlus, TRNSYS, TRACE, HAP, and others (Mao et al., 2013; Crawley et al., 2008). Forward and simulation methods have also been categorized based on varying complexities into benchmarking, degree day, bin, quasi steady-state, lumped parameter, and dynamic simulation methods (CIBSE, 2015). Each of the methods may require different time steps of climate data, such as annual, seasonal, monthly, daily, hourly, and even sub-hourly intervals. This study investigated forward and simulation methods only, since data-driven methods rely on actual data from buildings. A comprehensive review of energy modelling methods and tools can be found in the papers by Mao et al. (2013) and Crawley et al. (2008). From the above methods three modelling methods were selected, namely the modified bin method, degree day method (manual calculation methods under the forward method category) and dynamic simulation method (EnergyPlus), as potential candidate energy modelling methods to be used in the multi-fidelity modelling approach.

Case study design scenario

The three candidate energy modelling methods were used to estimate the energy consumption of a set of sixteen design alternatives for a hypothetical generic office building in four locations with a mix of hot, mild, cold, humid, and dry climates. The locations included Fairbanks, AK, Philadelphia, PA, Phoenix, AZ and Sydney, Australia. The building's fixed parameters included: gross area of 932 m^2; commercial office type; serving 50 people; lighting intensity 9.69 W/m^2; plug load intensity 14.42 W/m^2. Additionally, all of the sixteen design alternatives had the same slab on grade and roof construction as well as requirements for interior climate (e.g., interior temperature setpoints). Four variables namely wall type, window type, window-to-wall ratio and building shape (i.e., number of floors and their dimensions) with two options per variable were considered, resulting in sixteen total design combinations. Table 1 shows the variables, options, descriptions, and main attributes; Table 2 shows all the design option combination with associated numbers to identify each (ids). Note that the options were selected to represent reasonable higher or lower technical possibilities. This study's goal was not to create a code-compliant design, but rather to investigate the energy modelling methods' ability to simulate different conditions.

Table 1:Varied parameters for 16 building designs.

Variables	Options	Description	Attributes
Wall Type	Option A	Plaster, brick, plaster	U-value: 1.57 W/m^2K
	Option B	Brick, EPS, CMU, plaster	U-value: 0.44 W/m^2K
Window Type	Option A	Single glazing, 1/4 in pane	U-value: 3.19 W/m^2K; SHGC: 0.86
	Option B	Triple glazing, 1/4 in panes	U-value: 1.53 W/m^2K; SHGC: 0.56
Window-to-Wall Ratio (WWR)	Option A	Small window area	WWR: 0.2
	Option B	Large window area	WWR: 0.8
Building Shape	Option A	1 level	Dimensions: 3.7x45.7x20.4 m
	Option B	3 level	Dimensions: 11.0x10.2x30.5 m

Table 2: Building design options with corresponding variables.

Design id	Wall assembly	Glazing	WWR	Floors
1	Plaster, Brick, Plaster	Single	0.2	1
2	Brick, EPS, CMU	Single	0.2	1
3	Plaster, Brick, Plaster	Triple	0.2	1
4	Brick, EPS, CMU	Triple	0.2	1
5	Plaster, Brick, Plaster	Single	0.8	1
6	Brick, EPS, CMU	Single	0.8	1
7	Plaster, Brick, Plaster	Triple	0.8	1
8	Brick, EPS, CMU	Triple	0.8	1
9	Plaster, Brick, Plaster	Single	0.2	3
10	Brick, EPS, CMU	Single	0.2	3
11	Plaster, Brick, Plaster	Triple	0.2	3
12	Brick, EPS, CMU	Triple	0.2	3
13	Plaster, Brick, Plaster	Single	0.8	3
14	Brick, EPS, CMU	Single	0.8	3
15	Plaster, Brick, Plaster	Triple	0.8	3
16	Brick, EPS, CMU	Triple	0.8	3

Calculation and simulation setup

The calculation procedures for the modified bin (MB) and degree day (DD) methods were followed as prescribed by Knebel (1983) and ASHRAE (2009) respectively and computationally executed using Microsoft Excel. The histogram function in Microsoft Excel was used to convert TMY-3 weather data into 5-degree interval temperature bins to be used in the modified bin calculations. The same hourly temperature data was used to estimate the annual heating and cooling degree days to be used in the degree day method. The EnergyPlus™ (EP) simulations were run for four time-steps per hour, using the TARP and DOE-2 surface convection algorithms and the conduction transfer function heat balance algorithm. Zone and system sizing was auto-calculated for each weather file and design. The buildings were modelled using Revit 2017 and then exported into an EP input data file (IDF) format using Autodesk® Green Building Studio. The HVAC system setup did not export from Green Building Studio, and a default packaged variable-air-volume template in EP was used instead. HVAC system efficiency details from the same template were used in the system sizing calculations of modified bin and degree day methods as well. The annual energy use intensity (EUI) in kWh/m^2/year was calculated for the sixteen design alternatives using the above modelling methods. Subsequently, to gain better insight on the differences in energy estimates, results were then disaggregated in two categories, following EP's categorization schemes: by end-use (i.e., heating, cooling, lighting, equipment, and fans) and by loads (i.e., heat gains and losses associated with opaque surfaces, windows, infiltration, people, lighting, and equipment).

RESULTS

In our empirical study, MB and DD methods consistently yielded higher annual building energy use estimates than EP, although they showed similar trends for design-to-design comparisons. The results in Figure 1 show the total energy use intensity of each building design using the three methods for one of the four locations, Philadelphia, Pennsylvania, USA. The results are also disaggregated into individual end-uses as defined in the methods section. The results for this location show the predominant energy use for climate control, i.e. heating, cooling, and fans. The same trend was seen in other locations, although its contribution in warmer climates was smaller than in colder climates. The differences between individual methods generally show higher cooling demands in MB and DD results than EP, and this trend was even more evident in warmer climates. The calculated cooling demands were 275-699% higher using MB and DD methods for the design ids 1 through 12, and 171-266% in the 3 story, high window-to-wall ratio designs (ids 13 through 16). Heating demands were relatively similar between methods, although EP values were slightly higher (by 1 to 25% in Philadelphia) in most design scenarios across all locations. The overall energy demand estimated by MB and DD methods were 3-26% and 7-27% higher than that of the EP estimates, respectively, except for design id 14, where the MB estimate was 1.5% lower than EP.

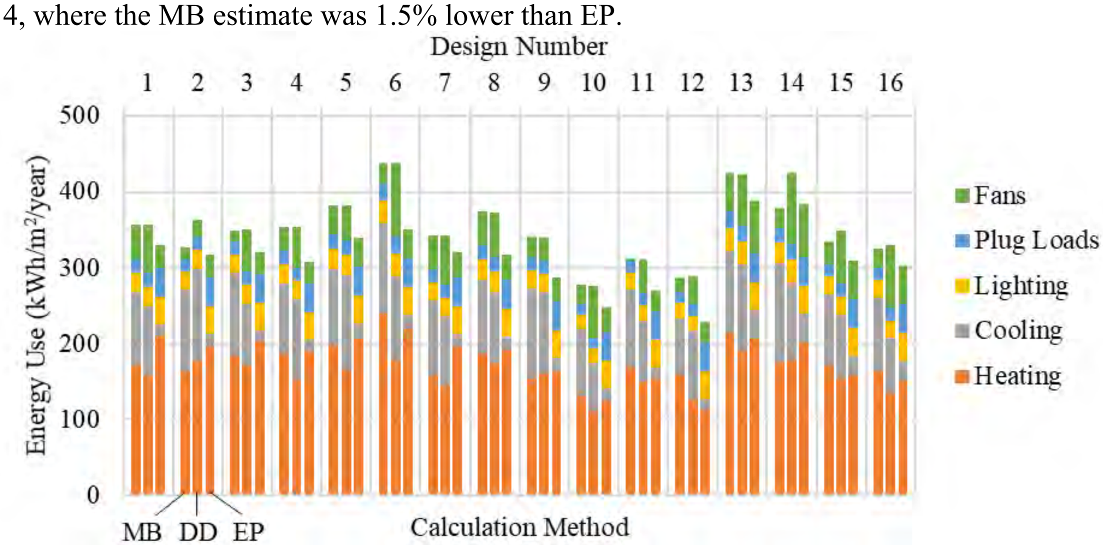

Figure 1. Example end-use results for Philadelphia, PA using three methods. Each design shows results from modified bin method (MB, left), degree day method (DD, middle), and EnergyPlus (EP, right).

Sample results for Philadelphia, PA disaggregated into individual loads are shown in Figure 2. Building designs and modelling methods are presented in the same order as in Figure 1. The results show that window heat gains and opaque surface heat losses are the primary contributors to heating and cooling demands in most design cases across all methods. The opaque surface heat transfer as well as heat gains from people, lights, and equipment (i.e., plug loads) are similar across the three methods, with sometimes slightly lower values from EP. The most noticeable difference is in the window gain values, which are 30-60% higher in MB and DD methods than in EP, especially in designs with high window-to-wall ratios. This trend is even more pronounced in the warmer climates of Phoenix and Sydney.

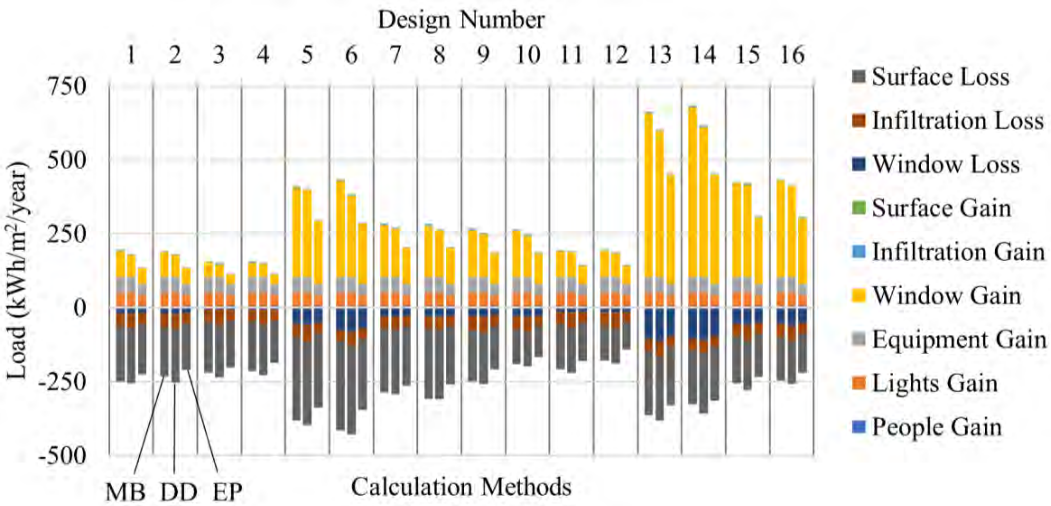

Figure 2. Example load results for Philadelphia, PA using three methods. Each design shows results from modified bin method (MB, left), degree day method (DD, middle), and EnergyPlus (EP, right).

DISCUSSION

Empirical results show that modified bin and degree day methods yield energy use intensity estimates of similar magnitude to each other but are relatively higher than results from the dynamic simulation method (EnergyPlus). Predictably, the differences in the results were traced to the heating and cooling end-uses, and specifically to the heat gain and heat loss through opaque (i.e., walls, floors, roofs) and window surfaces. It should be noted that the findings are specific to the medium office use type, default schedules and HVAC setup, and that the findings may not be applicable to all other design scenarios. It is also important to note that the temperature interval used for binning (5°C in our case) might impact the performance of the method by increasing or decreasing the load estimates. Future research may investigate other design scenarios and bin discretisations.

Plausible explanations for the differences in surface heat gains and losses could be due to each method's underlying treatment of convection, conduction and radiation. For example, degree day and modified bin methods assume steady-state heat transfer in their calculations, whereas EnergyPlus considers transient heat transfer in its calculations. Furthermore, our investigation revealed, although not presented here for brevity, that radiation contributes significantly to the heat gains/losses and that modified bin and degree day method use approximate calculation methods to account for radiation whereas EnergyPlus utilizes advanced calculation methods that account for long wave and shortwave radiation effects. Understanding the effects of the varying heat transfer methods on the energy estimates is part of our ongoing efforts.

CONCLUSIONS

Our empirical results showed trends in differentiation between methods that could be utilized in a multi-fidelity energy modelling design framework. Ongoing research is focusing on a more theoretical explanation of the methods' differences in the underlying heat transfer calculations (i.e., steady state and transient) as it pertains to the surface heat gains and losses. An in-depth understanding of these differences is necessary to determine how to sequence these energy modelling methods in terms of fidelity and how lower fidelity models will inform higher fidelity models. For example, using the approach of Miller et al. (2017), bounding mechanisms (i.e., a method for the lower-fidelity models to bound the more precise estimate from the higher fidelity model over the entire design space) will be required to eliminate non-optimal building designs from large sets of early design alternatives efficiently.

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