Towards A New Methodology for Rapidly Modelling Existing Buildings in EnergyPlus

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Abstract

Existing buildings have a high potential to increase their energy efficiency through retrofit projects. However, one of the most powerful tools for quantifying the impact of energy efficiency measures, building performance simulation, is rarely applied to existing buildings - in part due to the effort to develop calibrated models. The proposed methodology leverages commercial building archetype models to serve as a base model from which modifications are made to better represent an existing building. With this approach, the modelling efforts associated with building geometry, construction assemblies, HVAC systems, and scheduling are significantly reduced, and the modelling time can be reallocated to retrofit analysis. A case study of an 11-storey office building in Ottawa, Canada, was conducted and detailed in this paper. The rapidly built, calibrated model had a CV(RMSE) of 24.73% and NMBE of 0.68%. We expect the proposed methodology to be widely applicable to other buildings and promote the application of building performance simulation on existing buildings.

Introduction

Globally, the existing commercial building stock is responsible for 8% of all energy consumption and 11% of greenhouse gas (GHG) emissions (Global Alliance for Buildings and Construction, 2019). In the United States, these figures are estimated to be even more significant, with commercial buildings accounting for approximately 18% of primary energy use in 2018 (EIA, 2020). These buildings present a high potential for energy efficiency improvements through strategic retrofitting or recommissioning (Ardente et al., 2011; Chidiac et al., 2011; Ma et al., 2012).

Building performance simulation (BPS) can play a key role in transforming existing buildings. Some of the numerous benefits include investigating a full range of energy-saving retrofit options, testing profit measures against future weather scenarios, and accurately predicting energy savings (Berardi & Jafarpur, 2020; Heo et al., 2012; Ma et al., 2012). The effectiveness of BPS is demonstrated by Dasmeh and Gunay (2018), who identified that commercial energy audits rarely use calibrated BPS models to inform their recommendations, despite the immense benefit. They built a calibrated model of a case-study building that had previously undergone an energy audit. With their calibrated model, they were able to recommend energy-saving measures that could reduce the building's energy consumption by 50%, as opposed to findings from the audit (without BPS) that only identified 10% energy savings.

BPS tools simulate the performance of a building using approximations to simplify complex systems and processes; this inherently leads to uncertainty. However, difficulties in evaluating building properties that the user must input to the program (i.e., infiltration rate) lead to further uncertainty (Beausoleil-Morrison, 2021). To reduce this uncertainty when creating an energy model, it is critical that the user understands building engineering, especially for modelling older buildings. Moreover, a detailed BPS model often requires a significant amount of time from the modeller and leaves the building owner with a considerable expense. With these concerns in mind, a workflow is being proposed to reduce the number of user inputs and modelling time required for a BPS to achieve ASHRAE Guideline 14 standards for calibrated energy models.

Rather than building a model from a scratch or basic starting file (as one would do in a traditional BPS workflow), the modeller can manipulate the geometry of a building archetype model to create a unique base or starting point for each project. Then, one would quickly be able to conduct simulations, provide building-specific details and calibrate the base model to measured energy data. This approach can dramatically reduce the number of modelling parameters that are initially needed to be input, allowing modellers to simply update default assumptions or add further details, ultimately making more efficient use of their time. This newfound time can be redirected to a more precise calibration or thorough retrofit analysis.

Building archetype models (also commonly referred to as reference or prototype models) are conceptual models built in EnergyPlus software. There are currently three sets of archetype models published in North America (DOE 2011, 2020; University of Colorado Boulder, 2021). Each of these sets model 15 to 18 building types for 15 to 19 locations and includes two or three different vintages (range of construction dates) for each building. This results in many buildings in each set (500+). The models are constructed based on commercial building energy consumption survey

(CBECS) data from the United States of America and were initially assembled to investigate energy efficiency goals, develop energy codes, and serve as common models for researchers to study new technologies, advanced controls, daylighting, ventilation, and indoor air quality (Deru et al., 2011).

The intention of these archetypes is not to represent an individual building and they are not to be considered as a target. However, because they are built to represent typical building types under typical operation, or the median performance, they can be a practical starting point for building-specific changes to create a detailed representation of an existing building. The specific archetype models used in this methodology were developed by the United States Department of Energy (DOE) but are first generated and modified by an urban building energy modelling (UBEM) program called City Building Energy Saver (CityBES) before being exported and further developed in traditional EnergyPlus software.

CityBES was developed by Lawrence Berkeley National Lab, USA, and is available online (LBNL, 2016). The program has a user-friendly interface that does not require programming knowledge or expertise in BPS. It can simulate the performance of city-scale building stocks, and includes features for energy efficiency analysis, benchmarking, and planning (Chen et al., 2017).

Despite beginning the process with an export from a UBEM program, this methodology is significantly different from UBEM. UBEM tools like CityBES are intended to model hundreds to thousands of buildings simultaneously. The main interest is the aggregate energy consumption and usage patterns rather than building level details (Hong et al., 2016). Further, to remain computationally efficient and user-friendly, there are typically very few building-specific details provided to the program. Reinhart and Davila (2016) highlighted that energy predictions from these programs on the individual building level could be inaccurate by up to 69%.

The methodology in this paper is meant to build models with more detail and allow for impactful retrofit suggestions for individual buildings or a portfolio scale rather than a city scale. This could make BPS much more accessible to portfolio managers attempting to complete retrofits on multiple buildings. While the authors are actively researching this expandability, the scope of this paper is limited to the benefits of using this methodology for a single detailed model.

When modelling existing buildings, many of the input parameters may be unknown (e.g., infiltration rate, U-value, R-Value, etc.). Model calibration can be applied to determine the correct values of these unknowns. Calibration is the fitting of a model's energy outputs to measured data from the existing building by tuning the values of parameters until they represent the actual operating condition (Fabrizio and Monetti, 2015). Calibration for a single building can be done manually by changing one or more parameter values per simulation until the model correctly predicts the energy consumption to a satisfactory level. Alternatively, an automatic approach would conduct numerous unsupervised simulations while searching for the optimal parameter values based on a provided optimization objective (Coakley et al., 2014; Hamdy et al., 2016; Heo et al., 2012; Sun and Reddy, 2006). This paper will apply an automatic technique to further reduce the modelling time by allowing the calibration algorithm to find optimal input parameters.

The methodology is proposed to reduce the number of input parameters users must provide for building modelling, and significantly reduce the overall time required to build a calibrated energy model. This is possible without sacrificing the accurate representation of an existing structure and maintains the ability to reach the acceptable whole building calibration requirements of ASHRAE Guideline 14 (2014). There is also an excellent opportunity to expand the rapid modelling onto multiple buildings simultaneously or consecutively using this methodology.

Despite being limited to a single office building for this paper, the methodology can be applied to various commercial building types and multiple buildings simultaneously. As a result, BPS modellers can adopt this contribution to significantly reduce the number of tedious, manual inputs required in their workflow, allowing more time for detailed calibration, or retrofit analysis. The remainder of this paper will provide details on the methodology, discuss its application using a case study building, and conclude with a discussion and closing remarks.

Methodology

In this paper, the web-based tool for urban building energy modelling named City Building Energy Saver was employed to automate the time-consuming process of obtaining and specifying input parameters. The user provides some essential characteristics of a building, and the program generates an EnergyPlus input data file based on an appropriate archetype model. The key benefit of this program is that it generates archetype models that match a provided building footprint and allows users to export the associated input data file (IDF). This IDF can then be used offline in traditional EnergyPlus. The workflow is briefly explained in Figure 1.

Stage 1

The automated generation of a base model dramatically reduces the time of manually inputting building characteristics such as geometry, construction materials and assemblies, schedules, thermal zoning, and more. To do so, a dataset of building-specific details must be uploaded to CityBES. This dataset must include the building type (e.g., office), height, number of storeys, and year of construction. It also must have the building’s footprint (i.e., shape/size).

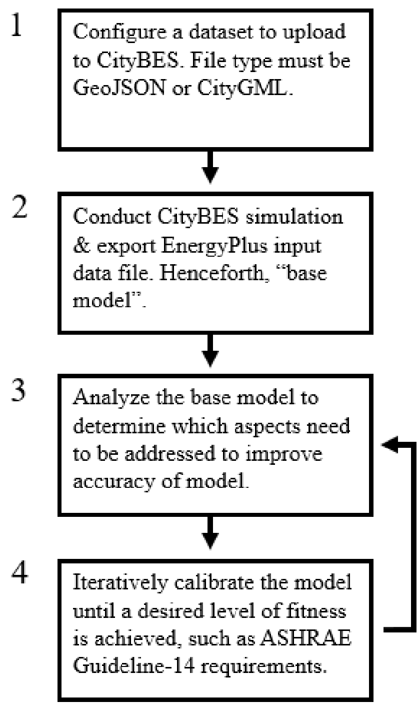

Figure 1: Flowchart depicting stages of proposed methodology

The building information can be input to a comma-separated values (CSV) file, and the footprint is generally gathered from geospatial vector data in the form of a shapefile. Then, using an open-source geographic information system (GIS) program called QGIS (QGIS, 2022), these files are synced together and exported as a GeoJSON file. For specific details on this process, the developers of the CityBES have a user guide available upon request that can assist with this stage. It is worth noting that because CityBES was designed to model multiple buildings simultaneously, this part of the methodology could be expanded such that multiple buildings are uploaded in one dataset, thus generating multiple input data files at the same time, further reducing time requirements associated with a typical geometry construction process.

Stage 2

The GeoJSON file is uploaded to CityBES to create a base model. Once the building is created in the program, users can easily change some parameters from their defaults, such as window-to-wall ratio (WWR) or HVAC system type. When the user is content with their model, a simulation will be conducted in the program. The program selects the optimal commercial reference building based on the provided building type, year of construction, and location (from geographical coordinates included in the shapefile). It then changes the archetype's height, footprint, and other building specifics based on the details provided in the dataset.

Upon completion of the simulation, an EnergyPlus IDF will have been created and become available for download. This IDF is complete with HVAC systems, materials, constructions, loads, and operation schedules from the archetype model. It has a considerable level of detail that would traditionally require a modeller significant time to achieve and can now serve as the base model that is updated with new building specific details.

Stage 3

Prior to applying changes to the baseline model, it is essential to review all the default components and understand the initial behaviour and performance of the base model. This allows for a better understanding of which attributes of the base model need to be addressed. An insightful visual aid for analysis is an energy map (Christensen, 1984). This figure shows the differences between the measured and simulated energy data for each timestep (e.g., hourly) to identify when the model performance deviates from the existing building's measured utility data. This tool can then be used iteratively during the next stage of the workflow.

Metrics other than the energy map can also be calculated during this stage for a quantifiable understanding of the base model's fitness to measured data. The normalized mean bias error (NMBE) and the coefficient of variation of the root mean squared error (CV(RMSE)) are commonly used by BPS practitioners and are recommended for determining compliance of the simulated data to measured data. These can be calculated as follows in equations 1 and 2:

$$NMBE = \frac{\sum_{i=1}^{N}(M_i - S_i)}{\sum_{1}^{N}(M_i)} \tag{1}$$

$$CV(RMSE) = \frac{RMSE}{\bar{M}} = \frac{\sqrt{\sum_{i=1}^{N}(M_i - S_i)^2/N}}{\bar{M}} \tag{2}$$

where M is the measured energy data point during the time interval; S is the simulated energy data point during the same time interval; N is the number of the time interval; $\bar{M}$ is the mean of measured values.

According to ASHRAE Guideline 14, the NMBE and CV(RMSE) for hourly calibration must be less than 10% and 30%, respectively. Therefore, the following case study seeks to improve the base model's results to achieve these fitness levels. However, in practice one can work towards any fitness level that is required for the project.

Stage 4

Once the base model is extracted from CityBES and initial analysis is conducted, the model calibration process begins. Until this point, the procedure is consistent and repeatable for any building; however, the process may vary at this stage, as specific details for each building will begin to influence decisions and make calibrating each model a unique task. It is essential to utilize known information about the building during this stage. Conducting an energy audit can provide plenty of insight into the building characteristics and performance to reduce the simulation's uncertainty (Ma et al., 2012). Ultimately, an audit may not yield all the required information, and modelling assumptions may need to be tuned for the model outputs to match the utility data. For example, some in-situ examinations such as fan depressurization tests for calculating the infiltration rate may be too time-consuming, costly, and disruptive, leaving infiltration as a large unknown parameter that must be calibrated.

To account for the unknown parameters, applying an optimization technique for automated calibration is recommended. This method can be scripted in MATLAB or Python programs to employ an optimization algorithm to minimize an objective function by varying the values of a set of parameters. Different objective functions can be set during the optimization process, though many seek to minimize the differences between measured and simulated energy. Using a genetic algorithm (GA) from the evolutionary algorithm family, this paper seeks to reduce the sum of CV(RMSE) from heating, cooling, and electrical energy as its objective function. Based on the provided parameters and search bounds, the process begins by creating a population of randomly generated individuals (i.e., values for each parameter). Next, the fitness function value (i.e., CV(RMSE) of the total energy usage) for all combinations of a generation is evaluated. The individuals with the lowest fitness function value are selected and used for recombination and mutation of the parameter values in the next generation, ideally improving on its objective with each generation. Eventually, the algorithm continues until the maximum number of assigned generations has been reached, or the acceptable fitness level has been achieved. The results from the individual simulation with the lowest CV(RMSE) are generally accepted as the new model inputs.

Case study

A case study is conducted on an 11-storey office building in Ottawa, Canada, to demonstrate this methodology. Built-in the 1980s, this building has a floor area of approximately 20,000 m^2 and is part of a district energy system that supplies steam for heating and chilled water for cooling. The building has a window-to-wall ratio (WWR) of 50% on all sides, 11 air handling units (one per floor) with no economizer mode, and operating zone-level VAV boxes paired with electric baseboards. All information regarding building specifications came from a previously completed energy audit report.

Yearly utility data for steam, chilled water, and electricity was available hourly for 2016. Subsequently, Ottawa's 2016 Actual Meteorological Year (AMY) weather file was used for energy simulation. This file has been created from weather station data by White Box Technologies (2021) from the local airport, which is 10 km away from the case study building.

Stages 1 and 2

The model for this building was generated from a shapefile (.shp) of the 2D building footprint, which was extracted from the City of Ottawa open-data repository. An excel file (.csv) with the information in Table 1 was also generated with the accurate building characteristics.

Table 1: Building characteristics.

Building Height	Number of Storeys	Year of Construction	Building Type
42m	11 (plus basement)	1985	Office

These two files were uploaded to QGIS, where they were merged and exported as a GeoJSON file. This file was then uploaded to CityBES. Once in the CityBES tool, the WWR was assigned to 50%, which was different from the default archetype model for an office building of the same vintage (23%). A simulation was then conducted in CityBES to generate the IDF, before being downloaded for analysis and manipulation on a local computer. The resulting geometry of the model once exported from CityBES is shown in Figure 2.

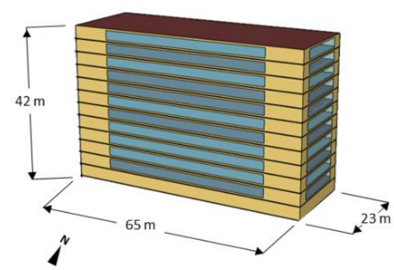

Figure 2: Geometry of case study building.

Stage 3

Prior to calibration, the model was determined to have a CV(RMSE) of 70.01% and NMBE of 44.14% when comparing the measured heating, cooling, and electricity data to the simulated. These results are well above the requirements of ASHRAE Guideline 14 for whole-building energy models calibrated with hourly energy data (30% and 10% respectively). Based on these results, the base model does not accurately represent the case study building. However, this was expected for the initial model because of the archetype-based method used to quickly construct it. As previously mentioned, the commercial building archetypes were designed to model the median energy use intensity (EUI) for each building type, vintage, and location they have been constructed for (Ye et al., 2020). Therefore, these results are acceptable because this model served only as a starting point. The next step of the methodology was to analyze the differences between simulated and measured

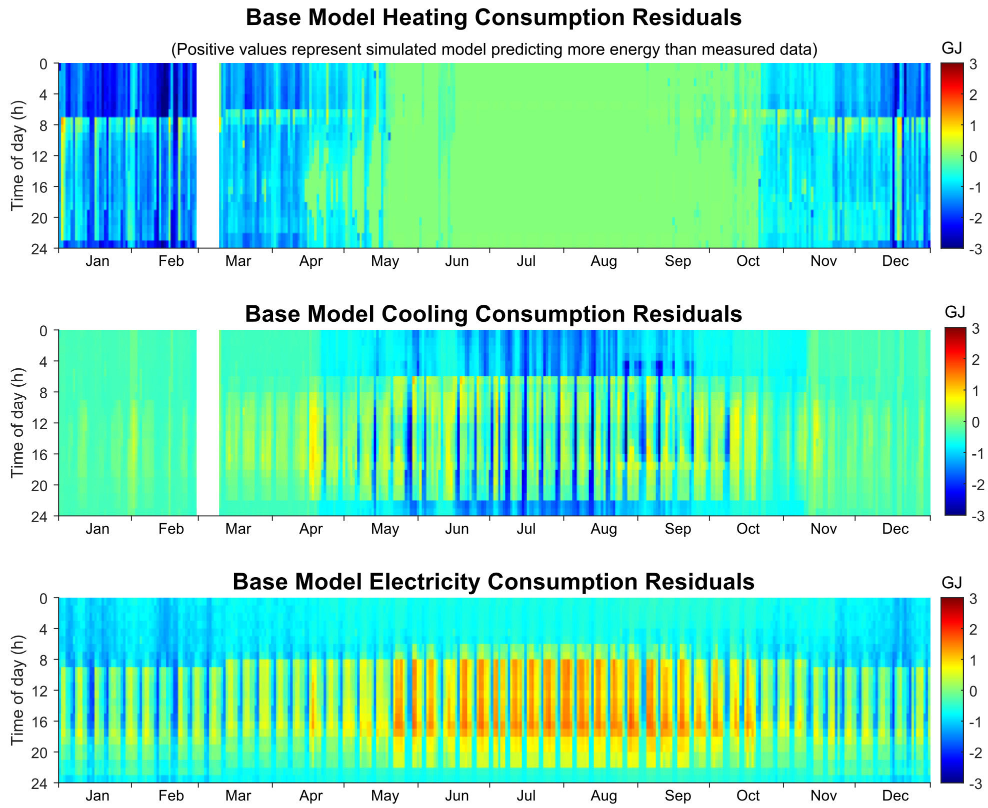

Figure 3: Base model energy map of the differences between simulated data and measured data. Blank sections depict missing utility data.

energy data before applying modifications during the calibration process to improve the model.

Another step during stage 3, was to review all the default components and understand the initial behaviour and performance. The energy map technique was applied to clearly visualize the energy trends on an hourly, weekly, and seasonal scale. The results of this initial plot are shown in Figure 3. One can see that the base model under-predicted the winter heating energy, especially during the unoccupied hours (i.e., 11 pm-7 am). For the summer months, cooling energy was also under-predicted during unoccupied hours (including weekends) but was slightly over-predicted during some occupied hours throughout the year. Lastly, the electricity consumption in the baseline model was consistently under-estimated during the unoccupied hours but greatly over-estimated for the occupied hours during the cooling season. A major takeaway from these results was that the schedules for all three energy end-uses were significantly different between the base model and the existing building. They would need to be addressed during calibration.

Stage 4

After reviewing the baseline model components, the first significant step to improve the model's accuracy was clear. The default variable air volume (VAV) HVAC system with a gas boiler and centrifugal chillers was replaced by the type of system present in the existing building. A district system supplies steam for heating and chilled water for cooling. This was important to correct because of how influential the HVAC system can be on an energy model's performance (Pérez-Lombard et al., 2008). This updated system immediately improved the electricity meter prediction because the base model included electric chiller energy, whereas the existing building does not have a chiller due to being part of a district system. The following steps follow a traditional approach for calibrating an energy model. First, utilize available information obtained from the building automation system's (BAS) existing data, on-site observations or measurements, and interviews with building operators. Then calibrate for the unknown parameter values (Heo et al., 2012). For this building, it was known that the HVAC equipment operated nearly 24/7, but occupant, lighting, and equipment schedules were not known. Table 2 shows the complete list of parameters used during the automatic calibration, including their base model values, final model values, and automatic calibration search bounds. These parameters were chosen as they are understood to have some of the most significant impacts on building energy consumption. In addition, results from a sensitivity analysis conducted by Derakhti et al. (2021) on

Table 2: List of parameters and values adjusted during automatic calibration

Parameters	Units	Base Model Values	Calibration Lower Bound	Calibration Upper Bound	Calibration Result Values
Window USI-Value	W/m^2-k	2.95	1	5	2.69
Window SHGC	---	0.39	0.2	0.8	0.46
Exterior Wall RSI-Value	m^2-k/W	2.33	1.0	4.5	2.45
Equipment Power Density	W/m^2	10.76	7	12	7.9
Lighting Power Density	W/m^2	16.14	7	12	7.12
Occupant Density	person/m^2	0.05	0.01	0.06	0.02
Fan Moter Efficiency	---	0.60	0.5	0.9	0.67
Outdoor Air Supply	m^3/s-person	0.0125	0.06	0.02	0.0944
Infiltration	$m^3/s\text{-}m^2$	0.00113	0.0006	0.002	0.00188
Equipment After Hours Fraction	---	0.4	0.1	0.6	0.547
Lighting After Hours Fraction	---	0.05	0.1	0.6	0.510

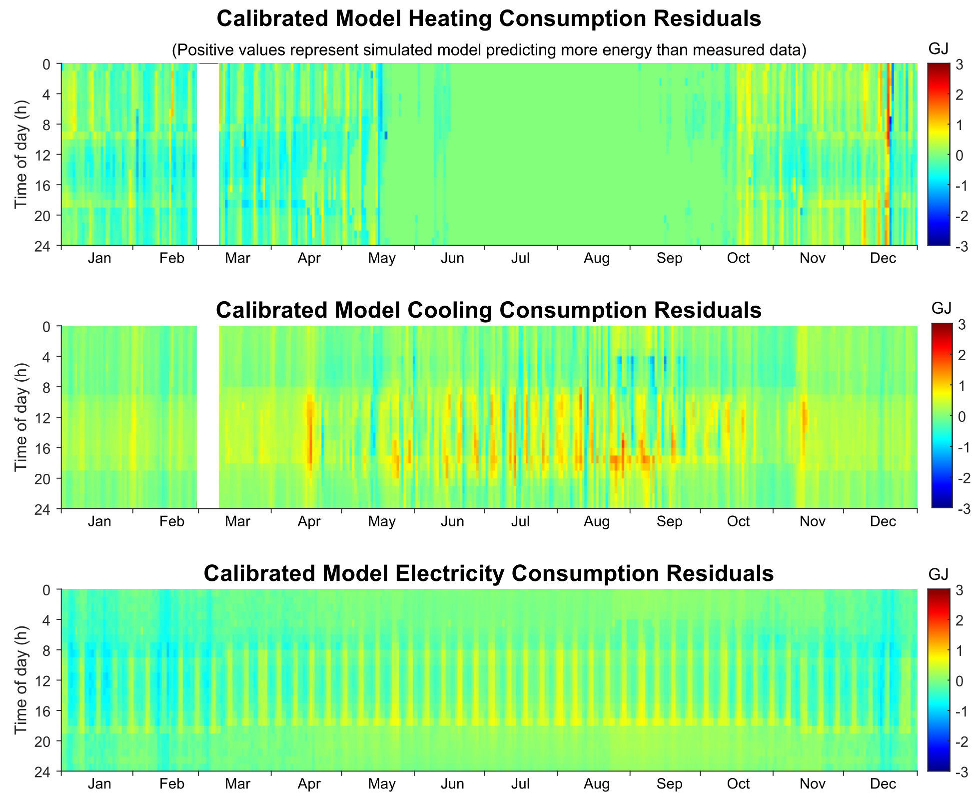

Figure 4: Calibrated model energy map of the differences between simulated data and measured data. Blank sections depict missing utility data.

similar parameters for a different model of the same building were also considered and suggest that due to the impact of the occupancy, operation condition, and changing material properties over time, the values of some unknown parameters do not have good compliance with the proposed value of in the standards and building codes. Therefore, this uncertainty and the impact of each parameter on the model output made it appropriate to include the multiple parameters in the automatic calibration.

After the calibration, a final CV(RMSE) and NMBE of 24.73% and 0.68% were calculated, respectively. These are significant improvements from the baseline model, but most importantly, represent an agreement between the simulated energy predictions and the hourly energy data from this building. Achieving these results demonstrates that this methodology can successfully model the behaviour of an existing building and meet the requirements of the ASHRAE Guideline 14 performance path for whole building calibration. Figure 4 shows the significant improvement of the simulated predictions with respect to the measured energy data. Notably, the size of energy residuals has been reduced for all types of energy, and there is rarely any variance more significant than 1 gigajoule during any hour.

With the completed calibrated model, a modeller could then conduct retrofit scenario analysis. Various modifications to the model could be implemented to determine an optimal package of changes that meet a client's desired sustainability goals and financial constraints. There are endless energy conservation measures that the model could be used to test. Some examples include replacing the lights, changing the operation schedule, or replacing the HVAC system. All of which could be done individually, and simultaneously to ensure the interactions are captured in the BPS.

Discussion

The amount of time the proposed methodology could save compared to a traditional "from scratch" workflow remains unquantified. This is because multiple factors influence building performance simulation, such as the modeller's skill and knowledge of the program, their comfort level with scripting environments to automate workflow components, availability of information for a building, and the general complexity of a building. As a result, modelling time will always vary from building to building and person to person. However, it is believed that this method can decrease the modelling effort by a substantial amount and is achieved by reducing the number of tedious inputs associated with geometry, materials, constructions, schedules, internal loads, and more. For example, a modeller with only intermediate-level skills was modelling the case study building, and it was not considered to have required a significant amount of time to achieve the presented results.

While the use of this methodology has many benefits, it is essential to discuss some limitations that have been identified. Buildings with complex geometry (e.g., varying exterior roof heights, an interior atrium, or complex thermal zones) will require extra modifications, possibly reducing the benefit of this streamlined modelling approach. This is due to the CityBES assumption that the provided footprint can be extruded vertically to the provided building height and then divided by the number of storeys such that each is an equal height. The archetype buildings also use a traditional five thermal zone method (four exterior, one core), which may not be optimal for all buildings. Another limitation is that unless the modeller has detailed information about the exterior envelope materials and construction, the model will accept the default constructions and should be calibrated for an effective thermal resistance. To model the exterior envelope with more detail would require more inputs, and therefore, more time, which this methodology is attempting to reduce. However, modelling the envelope with effective resistances is a common approach for existing buildings and may not influence the retrofit recommendations. This is because envelope-related energy conservation measures are often not prioritized or feasible due to the capital expense, disturbance to building occupants, and being embodied-carbon intensive (Ardente et al., 2011).

As with any building energy model, it is important to use engineering judgment to determine which aspects of the model need the most time dedicated to them and prioritize components that have the greatest effect on modelling the existing building's behaviour. While a detailed sensitivity analysis was not conducted for this case study, it could have benefited from one. Also, while components such as detailed wall constructions were not included in the case study, a modeller can choose to use as much or little detail as they see fit, depending on the use case of their model and the component's sensitivity.

While this methodology was only demonstrated on one building, it can be expanded to model multiple buildings simultaneously or consecutively. This can be achieved by providing a GeoJSON file to CityBES that has details (footprints, etc.) of multiple buildings, such that IDFs can be generated for all. Then building-specific details for each could be added to a level that is adequate for the intent of the analysis. This could be an effective way to model a portfolio of buildings with more detail than doing so with a UBEM, or the cost of a traditional detailed approach. The application of this methodology to other building types and climates can also be investigated in future work.

Conclusion

The proposed methodology significantly reduces the time and effort required to model existing buildings in EnergyPlus and the model accuracy was significantly increased with the use of automatic calibration. The value of the CV(RMSE) and NMBE for the annual energy consumption of the calibrated model were 24.73% and 0.68%, respectively. By automating the tedious and potentially unimportant components of model development using an archetype model as a base, the modeller can spend more time precisely calibrating the model, conducting a thorough retrofit analysis, or, alternatively, reducing the cost that is put on building owners or managers. These benefits promote the use of BPS on existing buildings to reduce the energy consumption of the built environment.

Acknowledgment

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