# A tool for evaluating the performance of simplified models for predictive control applications

Trent Hilliard, Lukas Swan
Dalhousie University, Halifax, Canada

## Abstract

This paper presents a method of determining the validity of simplified models for use in predictive control. As opposed to traditional statistical measures, a comparison of the model predictive control (MPC) performance of a high-fidelity model is used as the baseline for comparison. A single modelling technique is tested against several buildings in different climates to show the application of the tool. The savings achieved with the simplified model range from 84% to 101% of the high-fidelity model savings, based on climate and building type.

## Introduction

With a worldwide focus on the reduction of greenhouse gas (GHG) emissions, all sectors of industry are being investigated for energy efficiency and GHG reductions. Buildings represent a large sector of energy consumption, accounting for 40 % of energy use in the US (Perez-Lombard, Ortiz, & Pout, 2008). One avenue to reduce building energy consumption is that building controls have been evolving from traditional rule based control strategies that are independent of environmental factors to model predictive controls (MPC) that use upcoming weather forecasts to determine an optimal building control scenario. This is a growing field of research, with full literature reviews published by (Afram & Janabi-Sharifi, 2014), (Hilliard, Kavgic, & Swan, 2015), and (Wang & Ma, 2008).

MPC is reliant on a model of the building dynamics, and traditional building simulation tools (e.g. EnergyPlus, ESP-r) are often too cumbersome, take too long to calculate, or initial conditions cannot be set (U.S. Department of Energy, 2016), thus they become unsuitable for advanced controls algorithms in real-time. This leads to the use of simplified models for MPC, such as resistive-capacitive circuits (Gunay, O'Brien, & Beausoleil-Morrison, 2016), state-space (Kim & Braun, 2012), statistical models (Ferreira, Ruano, Silva, & Conceicao, 2012), and non-linear models (Schirrer, Brandstetter, Leobner, Hauer, & Kozek, 2016). The work of (Killian & Kozek, 2016) and (Privara, et al., 2013) indicate the importance of the choice of a building model for MPC, with no clear modelling choice as the best option (Killian & Kozek, 2016).

It is necessary to develop a tool to validate if a simplified model is accurate enough for a MPC approach. Traditional methods compare a model's prediction to that of either measured data or a higher fidelity model via statistical methods (such as mean absolute error (Gunay, O'Brien, & Beausoleil-Morrison, 2016) or normalized root mean square error (Privara, et al., 2013)), but don't let a user know what level of accuracy is required for MPC. Instead they rely on the principle that a more accurate model will provide better results. However, there is likely a level of accuracy that once exceeded will render no benefit to the MPC algorithm as the same optimization choice would be made once a minimum level of accuracy is achieved. An example is given in (Sourbron, Verhelst, & Helsen, 2103), where a 2$^{nd}$ order model achieves the same results as a 4$^{th}$ order model. Thus, a more applicable tool/method is required to determine the level of accuracy required by a simplified model to produce acceptable MPC results than solely statistical measures.

This paper proposes a method for determining the savings captured by a simplified building model in contrast to that of a high-fidelity model. It is similar to the works of (May-Ostendorp, Henze, Corbin, Rajagopalan, & Felsman, 2011) and (Coffey, 2013) who quantified the loss in performance when taking a computationally intensive MPC and translating it to an operationally viable look-up table. They show a loss of fidelity in the range of 13-28%. The case study presented in this paper uses 3 of the U.S. Department of Energy (DOE) archetype buildings (large office, medium office, and secondary school) (US Department of Energy, 2016), of 2 different construction vintages (new and pre-1980) in 4 climates (Chicago, Halifax, San Diego, Seattle) for a total of 24 buildings analysed. All the buildings are modelled using the same statistical method and control objective as outlined in the Methodology section. The goals of this study are to determine if the same modelling technique is applicable across a variety of buildings and climates, however a variety of models can also be considered as an expanded use of the methodology.

## Methodology

This section outlines the methodology used for the original rule based control (RBC) the high-fidelity model emulated MPC used as the baseline performance and simplified model MPC case.

### Rule-based Control

The DOE models come with a rule-based control strategy that involves night setback and modified weekend schedules. For this work the weekends were further modified to be purely in setback mode to simplify the MPC implementation. The setback period is from 22:00 to 06:00 Monday to Friday, and all day Saturday and Sunday. The setback temperature setpoints are 15.6 and 26.7 °C respectively, while the occupied setpoints are 21 and 24 °C, during the periods of 06:00 to 22:00 Monday-Friday. While the control period switches at 06:00 for RBC, most occupants do not arrive until 08:00, which is used as the target time for comfort.

**Emulated MPC**

A high-fidelity model predictive control strategy was required for usage as a baseline to evaluate the simplified model performance. For the case study in this paper, a morning start optimization was chosen for the predictive control benchmark. The benchmark was created by running EnergyPlus for all the possible morning start options available to a building to construct a database of potential solutions from the high-fidelity model. The solutions were generated from the original rule-based control strategy of the building (turn on at 06:00 for occupancy at 08:00), and divided into 15 minute intervals to match the timestep for the simplified model MPC. This leads to a set of 9 possible start times per day (see Figure 1). These solutions are then parsed on a day by day basis to find the optimal start time (setpoint transition and ventilation activation) for that specific day. The optimal solution is the start time that consumes the least amount of energy over the 1 day period, and meets the thermal comfort band of 20.75-24.25 °C at 08:00. The methodology relies on the understanding that the building dynamics converge during the steady daytime period (shown in Figure 1). This allows for stitching together of days from various simulations to form a complete yearlong simulation. This method represents what a perfect MPC simulation would chose. Examples of the morning start transitions can be found in Figure 1.

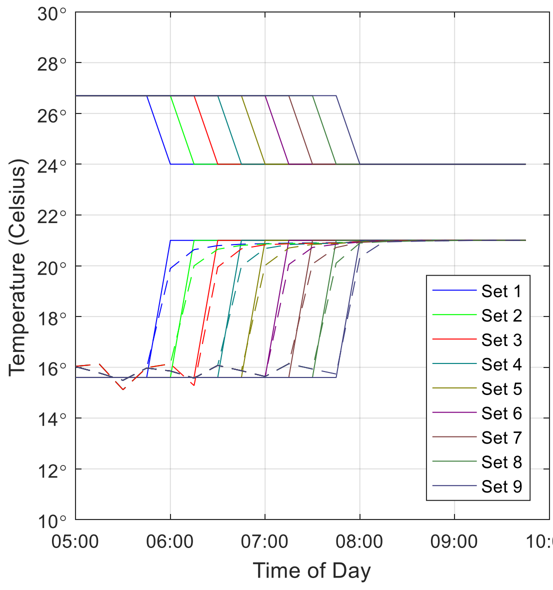


*Figure 1 Morning start optimization options setpoints (solid) and temperatures (dashed)*

**Simplified model predictive control**

After development of a benchmark for MPC performance, a predictive control algorithm was then employed. For this paper, a simplified brute force search of all possible start times was conducted, with the control options outlined in Table 1. For reference, the setback setpoints are 15.6 and 26.7 °C, while the daytime setpoints were 21 and 24 °C respectively (same as RBC). A statistical model of the building was developed using the *randomForest* (Liaw & Wiener, 2002) package within statistical software *R*. The model was used to evaluate if the thermal comfort requirement was met by predicting building average temperature, and to predict energy consumption of the building to find the least intensive path. The inputs for statistical model were time of day, day of week, current ambient conditions (air temperature, humidity, solar radiation), current zone air setpoints, current air temperature, current energy consumption (both thermal and electrical), and zone air setpoints for the next timestep. The model would then predict the future building average temperature and the energy consumption for use with the optimization algorithm. The model was trained with 9 sets of data, representing the potential start times for the algorithm. Figure 2 is an example of the training control schedules.

*Table 1 MPC morning start options (only heating shown)*

| | 6:00 | 6:15 | 6:30 | 6:45 | 7:00 | 7:15 | 7:30 | 7:45 | 8:00 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 21 |
| 2 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 21 | 21 |
| 3 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 21 | 21 | 21 |
| 4 | 15.6 | 15.6 | 15.6 | 15.6 | 15.6 | 21 | 21 | 21 | 21 |
| 5 | 15.6 | 15.6 | 15.6 | 15.6 | 21 | 21 | 21 | 21 | 21 |
| 6 | 15.6 | 15.6 | 15.6 | 21 | 21 | 21 | 21 | 21 | 21 |
| 7 | 15.6 | 15.6 | 21 | 21 | 21 | 21 | 21 | 21 | 21 |
| 8 | 15.6 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 |
| 9 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 |

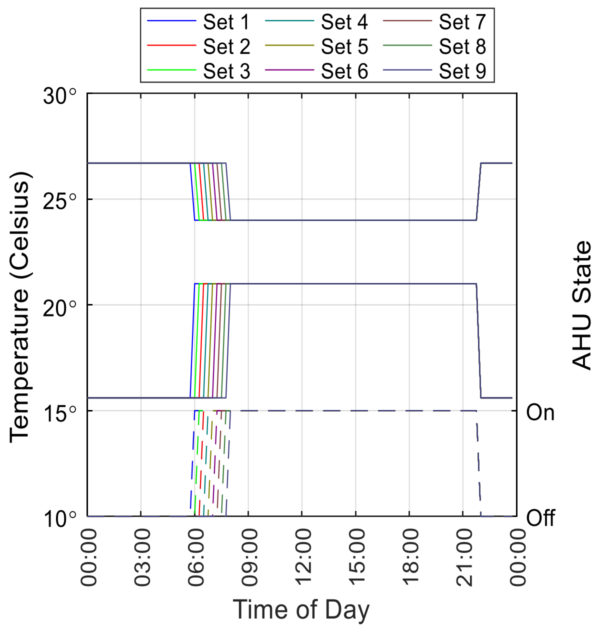


*Figure 2 Model training data control schedules*

The simplified model prediction performance is shown in Figure 3 for power, and Figure 4 for temperature for the large new office in Halifax. Figure 3 shows the average annual power for both thermal and electrical energy, along with the average residual in power predictions for each timestep for Monday-Friday. As shown, the electrical predictions show almost no residual, while the thermal energy shows slight absolute average error (peak around 10% at 06:00) at the initial change, related to a typical under prediction at that time. The spread of absolute errors goes to a peak of 150 kW for electricity compared to a peak consumption of 1500 kW, while thermal energy has a peak absolute error of 1400 kW compared to a consumption of 4100 kW. For the temperature predictions shown in Figure 4, the trend is to slightly under predict during the transition period, but with an absolute magnitude of 0.2 °C or less. A peak absolute error of 1 °C is realized. Similar trends are realized for the other buildings in the study. A statistical measure of weighted absolute percentage error (WAPE) was also investigated and is detailed by Equation 1. The results for the buildings studied is given in Table 2, which show a high level of consistency between the simplified models. Based on the consistency in statistical results, it is expected that the MPC performance should also be quite similar. The same simplified model methodology was used in (Hilliard, Swan, Kavgic, Qin, & Lingras, 2016) for readers looking for further details, and is the reason the model was chosen.

$$WAPE_{\text{Period}} = \frac{\sum_{\text{Period}} |Predicted - Actual|}{\sum_{\text{Period}} Actual} \qquad (1)$$

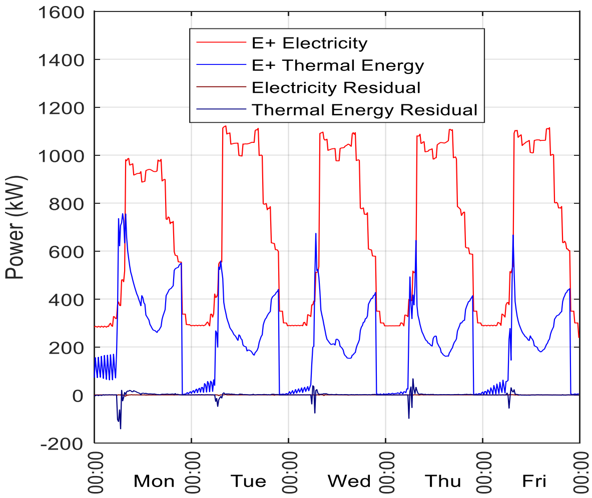


*Figure 3 Simplified model energy prediction performance for the large new office in Halifax*

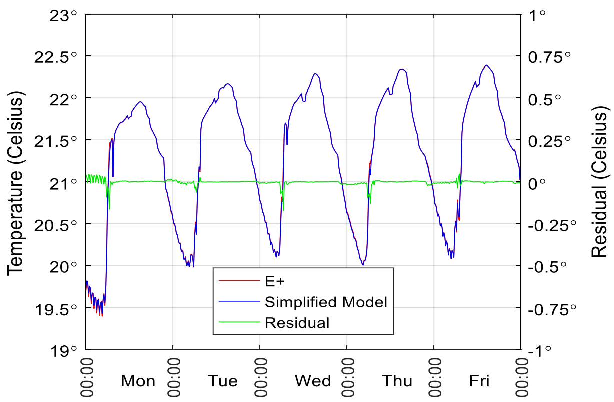


*Figure 4 Simplified model temperature prediction performance for the large new office in Halifax*

*Table 2 Weighted absolute percentage errors*

| **Model** | **Electricity** | **Thermal Energy** | **Temperature** |
|---|---|---|---|
| **Large Office** | | | |
| Chicago: New | 0.1% | 2% | < 0.1% |
| Seattle: New | 0.1% | 1% | < 0.1% |
| San Diego: New | 0.1% | 3% | < 0.1% |
| Halifax: New | 0.1% | 3% | < 0.1% |
| Chicago: Pre-1980 | 0.1% | 2% | < 0.1% |
| Seattle: Pre-1980 | 0.1% | 1% | < 0.1% |
| San Diego: Pre-1980 | 0.1% | 2% | < 0.1% |
| Halifax: Pre-1980 | 0.1% | 2% | < 0.1% |
| **Medium Office** | | | |
| Chicago: New | 0.1% | 1% | < 0.1% |
| Seattle: New | 0.1% | 2% | < 0.1% |
| San Diego: New | 0.1% | 2% | < 0.1% |
| Halifax: New | 0.1% | 1% | < 0.1% |
| Chicago: Pre-1980 | 0.1% | 3% | < 0.1% |
| Seattle: Pre-1980 | 0.1% | 2% | < 0.1% |
| San Diego: Pre-1980 | 0.1% | 5% | < 0.1% |
| Halifax: Pre-1980 | 0.1% | 2% | < 0.1% |
| **Secondary School** | | | |
| Chicago: New | 0.1% | 1% | < 0.1% |
| Seattle: New | 0.1% | 1% | < 0.1% |
| San Diego: New | 0.1% | 1% | < 0.1% |
| Halifax: New | 0.1% | 1% | < 0.1% |
| Chicago: Pre-1980 | 0.1% | 1% | < 0.1% |
| Seattle: Pre-1980 | 0.1% | 1% | < 0.1% |
| San Diego: Pre-1980 | 0.1% | 1% | < 0.1% |
| Halifax: Pre-1980 | 0.1% | 1% | < 0.1% |

Similar to the emulated MPC case, an objective of minimizing energy consumption while ensuring thermal comfort was achieved by 08:00 was maintained. The cost function to be minimized is outline in Equation 2, with the constraint in Equation 3. Assuming that the original band of 21 and 24 °C guarantees comfort, a 0.25 buffer allows for up to 25% of the building to deviate by 1 °C, which is slightly larger to ASHRAE 55 percentage of people dissatisfied values of 10%. This buffer is applied only for the initial morning occupancy of 08:00 when the building is ramping towards the target temperature. Thus a 0.25 deviation seemed more appropriate than a 0.1, as it represents 95% of the transition from the setback value (15.6) to the occupied value (21). It is assumed that the fluctuations by zones from setpoints are minimized due to the HVAC systems always running together, and proper system design employed by the DOE archetype buildings. A perfect weather forecast was used, utlizing the same weather file and pattern as for the emulated MPC.

$$Cost = \sum_{i=1}^{n} Energy(i) \quad (2)$$

$$20.75 < T(08:00) < 24.25 \quad (3)$$

The optimization is conducted for the morning start period beginning at 05:45 until 07:30. A receding prediction horizon is used between the current time and 08:00, leading to a total of 9 possible paths at 05:45, down to 2 possible solution paths at 07:30 (turn on at 07:45 or 08:00). An example of the options evaluated at 05:45 is shown in Table 1. The cost of all options is evaluated at each timestep, with a penalty term of 1e50 implemented to the cost function if the thermal comfort criteria is not met. The minimum cost option is then implemented for the current timestep values, and if the system is not turned on (i.e. still in unoccupied mode), the MPC is then run at the next timestep. This allows for the use of updated forecast information for future timesteps. If the system is turned on, it will then stay on for the remainder of the day and the optimization loop is complete. An additional override was added that if the minimum cost is greater than 1e50 (i.e. no option meets thermal comfort), then the system will turn on to attempt to meet the thermal comfort criteria.

For the simplified MPC approach, a co-simulation is run where EnergyPlus is used as the ‘real’ building, and the simplifeid model within R is used to determine the optimal start time as described. A diagram outlining the linkage between the MPC optimizer and system model (done in R) and the ‘real’ building (EnergyPlus) is given in Figure 5.

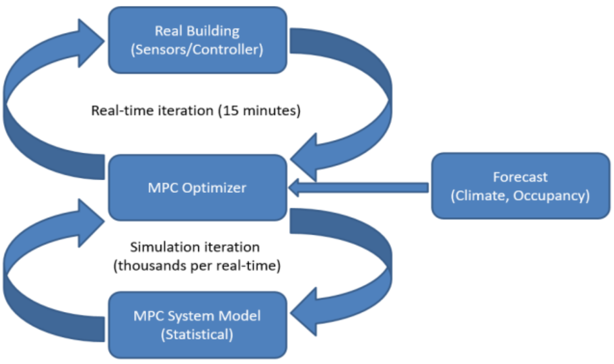


*Figure 5 MPC System architecture*

## Results

The methodology was applied to 24 DOE archetype buildings consisting of 3 building types (large office, medium office, and secondary school), 2 vintages (new construction and pre-1980 construction), in 4 weather climates (Chicago, Halifax, San Diego, Seattle). The analysis of results can be divided into 2 main sections: thermal comfort and energy consumption.

### Thermal Comfort

The first aspect analysed was if the thermal comfort constraint was being properly maintained by both the emulated MPC and the simplified MPC.

Table 3 outlines the number of weekday mornings where comfort was not met at 08:00, as well as the number of kelvin hours (Kh) of discomfort measured in the building average temperature during the occupied period (08:00 to 22:00). The emulated MPC case maintains the same number of violations as the original RBC scenario, with the simplified MPC showing a minor increase in violation counts. A similar trend is found when analysing the Kh numbers, with the emulated MPC showing a small rise from the RBC scenario, with the simplified MPC showing a larger increase in discomfort hours.

A second analysis of the results can look at both building type and climate location to determine if there are any buildings or climates for which the simplified model does not perform as well. As shown, the secondary schools show the poorest performance (most times comfort not met and largest Kh), likely due to their higher surface area to volume ratio. A second trend that is noticeable is the worse performance of the pre-1980 buildings in contrast to the new construction. This is due to the weaker envelopes that contain less insulation and have higher infiltration loads, which lead to a larger range of solutions that the simplified models may not fully capture (i.e. these buildings are more sensitive to external inputs).

An example of the morning comfort at 08:00 for each weekday for the large new office building in Halifax is outlined in Figure 6. As shown, the RBC and emulated MPC results always lie within the comfort bands, while the simplified MPC struggles to correctly identify the start time of the coldest of days. Of note is that the temperature violations are quite small (under 1 °C), which indicates a minor error in activation time. An example of this is shown in Figure 7, where the simplified MPC is 1 timestep delayed from the emulated MPC and thus does not meet the thermal comfort criteria.

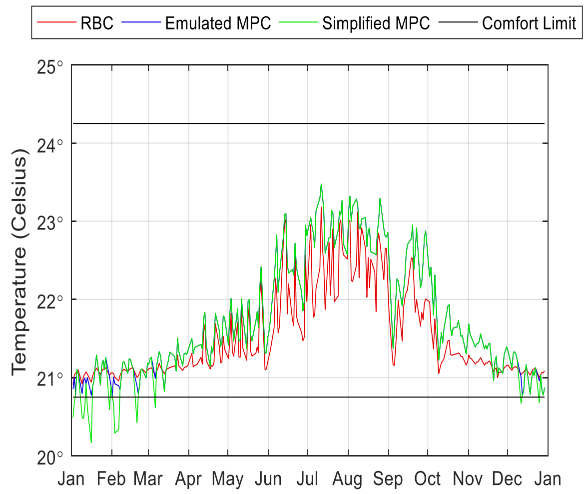


*Figure 6 Large new office Halifax 08:00 temperature*

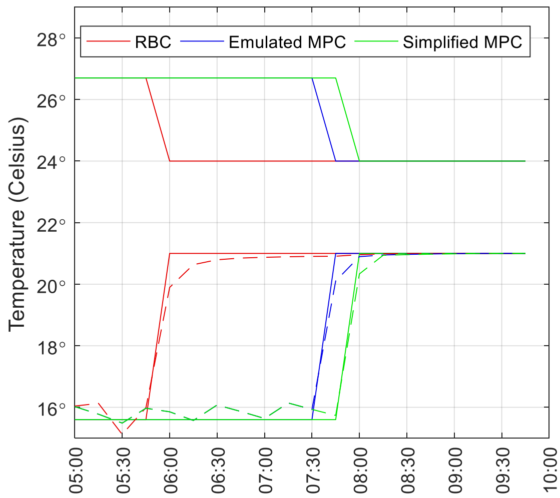


*Figure 7 Sample winter morning start optimization setpoints (solid) and temperatures (dashed)*

## Energy Consumption

After investigating the thermal comfort criteria performance of the emulated and simplified MPC scenarios, an energy consumption analysis was conducted to provide a second key benchmark on performance. Based on the close matches between the emulated MPC and simplified model MPC, a similar level of energy consumption savings was expected. As shown in Table 4, the simplified MPC captures between 84 and 101% percent of the emulated MPC savings. Cases of savings greater than 100% represent when the thermal comfort criterion is not satisfied, and extra energy is saved at the expense of occupant comfort. Similar to the comfort violations, the pre-1980 secondary schools show the lowest level of emulated MPC performance tracking, with all other building lying in the 97-101% region. There appears to be little distinction between vintages, which differs from the thermal comfort criteria. When comparing the savings of the MPC scenarios to the RBC case, between a 6 and 16% reduction in energy consumption is realized. Once again, the secondary schools stand out as having the largest energy savings when compared to RBC, which is related to their higher surface area to volume ratio that leads to larger influence of external weather parameters. In terms of climate, the office buildings see larger savings in colder climates (Halifax, Seattle), while the secondary schools see larger savings in the warmest climates (San Diego).

A monthly analysis of HVAC energy consumption divided into thermal energy and electricity is provided in Figure 8 for the large new office in Halifax. As shown, the large thermal energy consumption during the cold months for the office verify why the colder climate buildings experienced the largest level of energy consumption reduction. This is due to the larger decreases experienced in the winter months compared to the warmer summer months. This conclusion is further verified by Figure 9 (winter) and Figure 10 (summer), which highlight the timestep scale savings for the large new office in Halifax. Of note is that the summer (Figure 10) scale of power is an order of magnitude lower than that of the winter day (Figure 9). A second reason for the increased winter savings is that in the winter, the energy values converge by 12:00, where an offset (albeit small) exists until 18:00 during the summer.

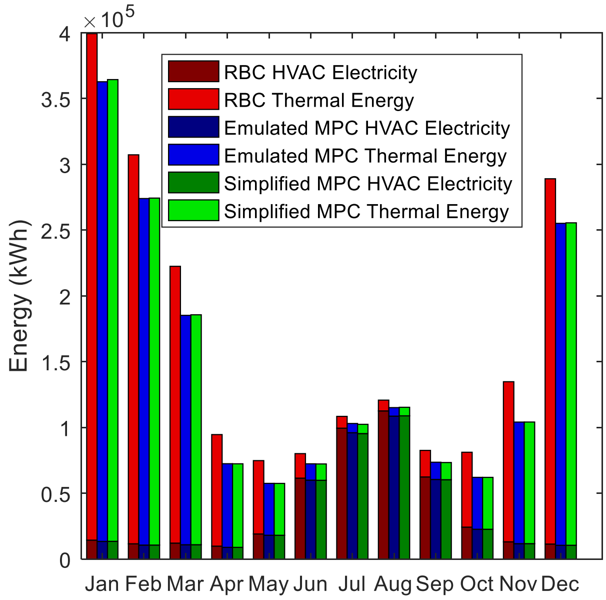


*Figure 8 Large new office in Halifax monthly HVAC energy*

## Conclusion

The results in this paper show that using a simplified building model can capture 84-101% of the energy savings for a morning start optimization utilizing a high-fidelity model. The results show that the simplified modelling methodology used appears most suitable for office buildings, where the simplified models capture 97-101% of the emulated MPC savings. While this paper uses the same modelling technique and applies it to various buildings and climates to assess its suitability for each variation, a series of different models can be tested on a single building and climate to find the most suitable model. This can also be used in conjunction with statistical methods (such as in (Gunay, O'Brien, & Beausoleil-Morrison, 2016)) to determine the level of accuracy/complexity required by the simplified model to achieve comparable results to a detailed building model. A limitation of the method is that it can only be used for once a day optimizations that have a sufficient settling time for state convergence (due to the piece-wise building of the emulated MPC case), and it takes longer to assess than traditional statistical method as it can only be conducted after the MPC has been run, as opposed to after a simplified model has been trained. Due to requiring MPC to be run for analysis, ensuring that the MPC is properly configured is also a requirement for the method. The results are also specific to the objective function used. The method does also require the effort to create a high-fidelity model as opposed to just a simplified model used by MPC, however the advanced model can be used to better verify overall performance than just comparison to previous measured data, as it can isolate the effects of weather and occupancy.

While the statistical model fit of WAPE showed similar prediction performance for all simplified models, the MPC performance varied, in particular the secondary schools. These variations in performance highlight why the use of statistical measures alone may not be sufficient in determining model suitability for MPC, as the statistical results were similar for all buildings, but the MPC performance differed.

While an optimized morning start objective was analysed in this work, any once a day optimization with convergence prior to the next optimization window can utilize the emulated MPC approach (such as free cooling).

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*Table 3 Temperature violation count at 08:00 and occupied Kh of discomfort (lower is better)*

| Building Type | Vintage | Location | RBC Violations | RBC Kh | Emulated MPC Violations | Emulated MPC Kh | Simplified MPC Violations | Simplified MPC Kh |
|---|---|---|---|---|---|---|---|---|
| Large Office | New | Chicago | 0 | 0.6 | 0 | 2.1 | 6 | 2.7 |
| | | Halifax | 0 | 0.3 | 0 | 1.3 | 15 | 3.1 |
| | | San Diego | 0 | 0.9 | 0 | 1.2 | 0 | 1.2 |
| | | Seattle | 1 | 0.4 | 1 | 1.2 | 7 | 2.5 |
| | Pre | Chicago | 0 | 1.0 | 0 | 2.9 | 6 | 3.3 |
| | | Halifax | 0 | 0.3 | 0 | 2.2 | 11 | 3.2 |
| | | San Diego | 6 | 72.9 | 1 | 74.9 | 1 | 75.0 |
| | | Seattle | 0 | 0.7 | 0 | 2.5 | 14 | 4.0 |
| Medium Office | New | Chicago | 0 | 0.0 | 0 | 1.1 | 3 | 1.2 |
| | | Halifax | 0 | 0.0 | 0 | 0.9 | 4 | 1.1 |
| | | San Diego | 0 | 0.7 | 0 | 1.0 | 0 | 1.0 |
| | | Seattle | 0 | 0.0 | 0 | 0.6 | 9 | 1.6 |
| | Pre | Chicago | 0 | 0.1 | 0 | 3.6 | 16 | 5.0 |
| | | Halifax | 0 | 0.2 | 0 | 2.3 | 1 | 2.4 |
| | | San Diego | 0 | 8.1 | 0 | 12.7 | 16 | 14.5 |
| | | Seattle | 0 | 0.3 | 0 | 1.8 | 4 | 2.2 |
| Secondary School | New | Chicago | 9 | 20.0 | 9 | 26.9 | 25 | 30.4 |
| | | Halifax | 3 | 3.6 | 3 | 6.1 | 22 | 9.6 |
| | | San Diego | 0 | 51.6 | 0 | 62.2 | 23 | 66.9 |
| | | Seattle | 3 | 3.1 | 3 | 4.9 | 19 | 7.9 |
| | Pre | Chicago | 4 | 21.1 | 4 | 37.4 | 6 | 31.8 |
| | | Halifax | 1 | 2.0 | 1 | 7.6 | 4 | 3.8 |
| | | San Diego | 0 | 40.7 | 0 | 162.1 | 0 | 121.5 |
| | | Seattle | 2 | 5.5 | 2 | 33.5 | 4 | 18.7 |
| Average | | | 1 | | 1 | | 9 | |

*Table 4 Total HVAC energy consumption [kWh]*

| Building Type | Vintage | Location | RBC | Emulated MPC | Emulated MPC % Savings | Simplified MPC | Simplified MPC % Savings | Simplified MPC % of Emulated MPC savings |
|---|---|---|---|---|---|---|---|---|
| Large Office | New | Chicago | 2206460 | 1998638 | 91% | 2000022 | 91% | 99% |
| | | Halifax | 1994935 | 1739024 | 87% | 1737065 | 87% | 101% |
| | | San Diego | 1041931 | 978554 | 94% | 979059 | 94% | 99% |
| | | Seattle | 2286225 | 1992591 | 87% | 1988399 | 87% | 101% |
| | Pre | Chicago | 3134156 | 2878934 | 92% | 2880914 | 92% | 99% |
| | | Halifax | 3041339 | 2731350 | 90% | 2735831 | 90% | 99% |
| | | San Diego | 1764987 | 1614020 | 91% | 1612556 | 91% | 101% |
| | | Seattle | 2771791 | 2391510 | 86% | 2391649 | 86% | 100% |
| Medium Office | New | Chicago | 289205 | 260937 | 90% | 261313 | 90% | 99% |
| | | Halifax | 259552 | 230605 | 89% | 231122 | 89% | 98% |
| | | San Diego | 119387 | 109715 | 92% | 109748 | 92% | 100% |
| | | Seattle | 166222 | 139760 | 84% | 139608 | 84% | 101% |
| | Pre | Chicago | 465858 | 433144 | 93% | 433815 | 93% | 98% |
| | | Halifax | 425015 | 389177 | 92% | 390181 | 92% | 97% |
| | | San Diego | 247672 | 226871 | 92% | 226792 | 92% | 100% |
| | | Seattle | 297104 | 263134 | 89% | 263554 | 89% | 99% |
| Secondary School | New | Chicago | 3262328 | 2876523 | 88% | 2885614 | 88% | 98% |
| | | Halifax | 3572314 | 3068181 | 86% | 3062854 | 86% | 101% |
| | | San Diego | 1214670 | 1011027 | 83% | 1010191 | 83% | 100% |
| | | Seattle | 2283125 | 1864935 | 82% | 1858703 | 81% | 101% |
| | Pre | Chicago | 3878070 | 3470502 | 89% | 3537452 | 91% | 84% |
| | | Halifax | 4195280 | 3653240 | 87% | 3727095 | 89% | 86% |
| | | San Diego | 1575572 | 1290026 | 82% | 1317726 | 84% | 90% |
| | | Seattle | 3007301 | 2529690 | 84% | 2598904 | 86% | 86% |

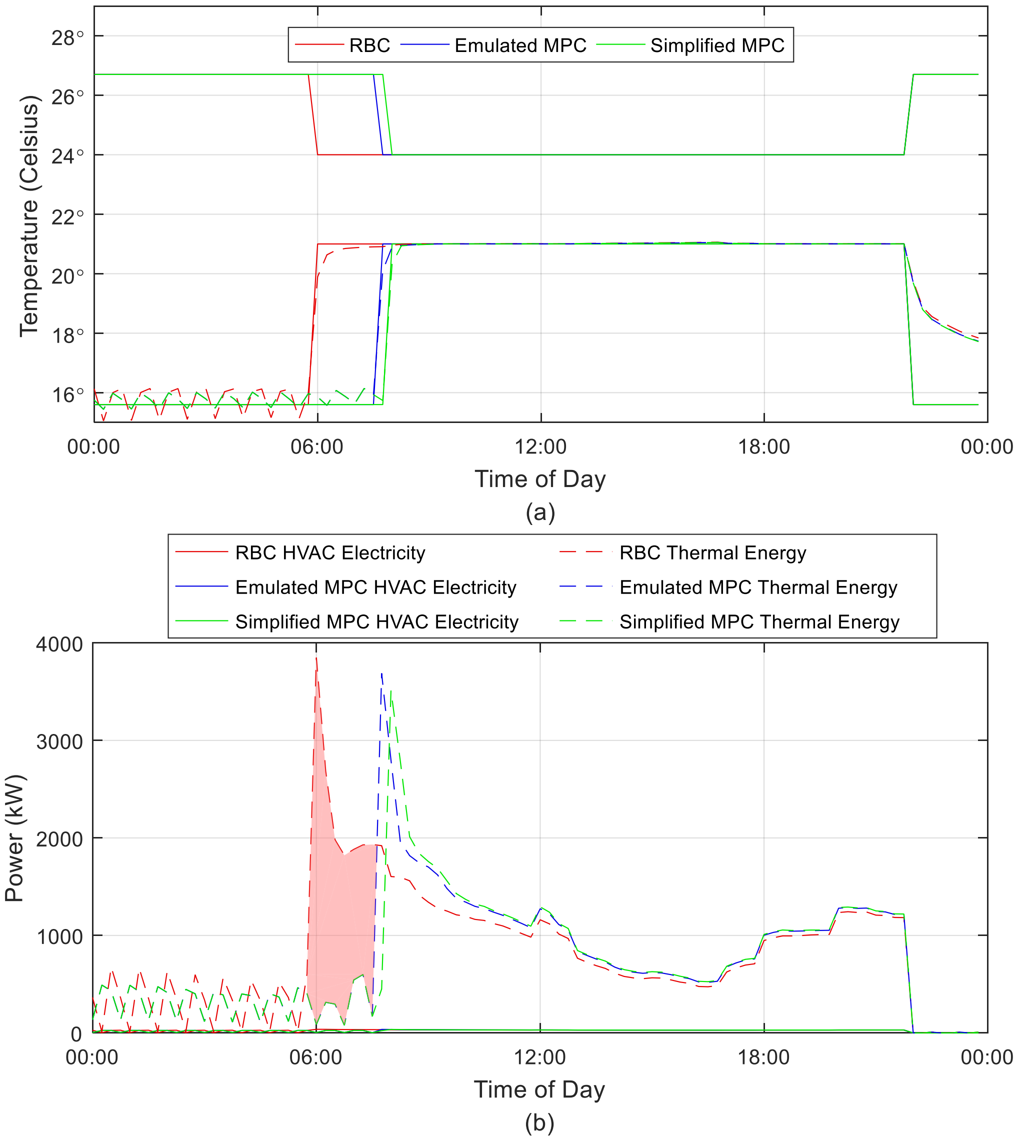


*Figure 9 New large office Halifax winter timestep analysis (a) Temperatures (setpoints are solid, temperature is dashed) and (b) Power*

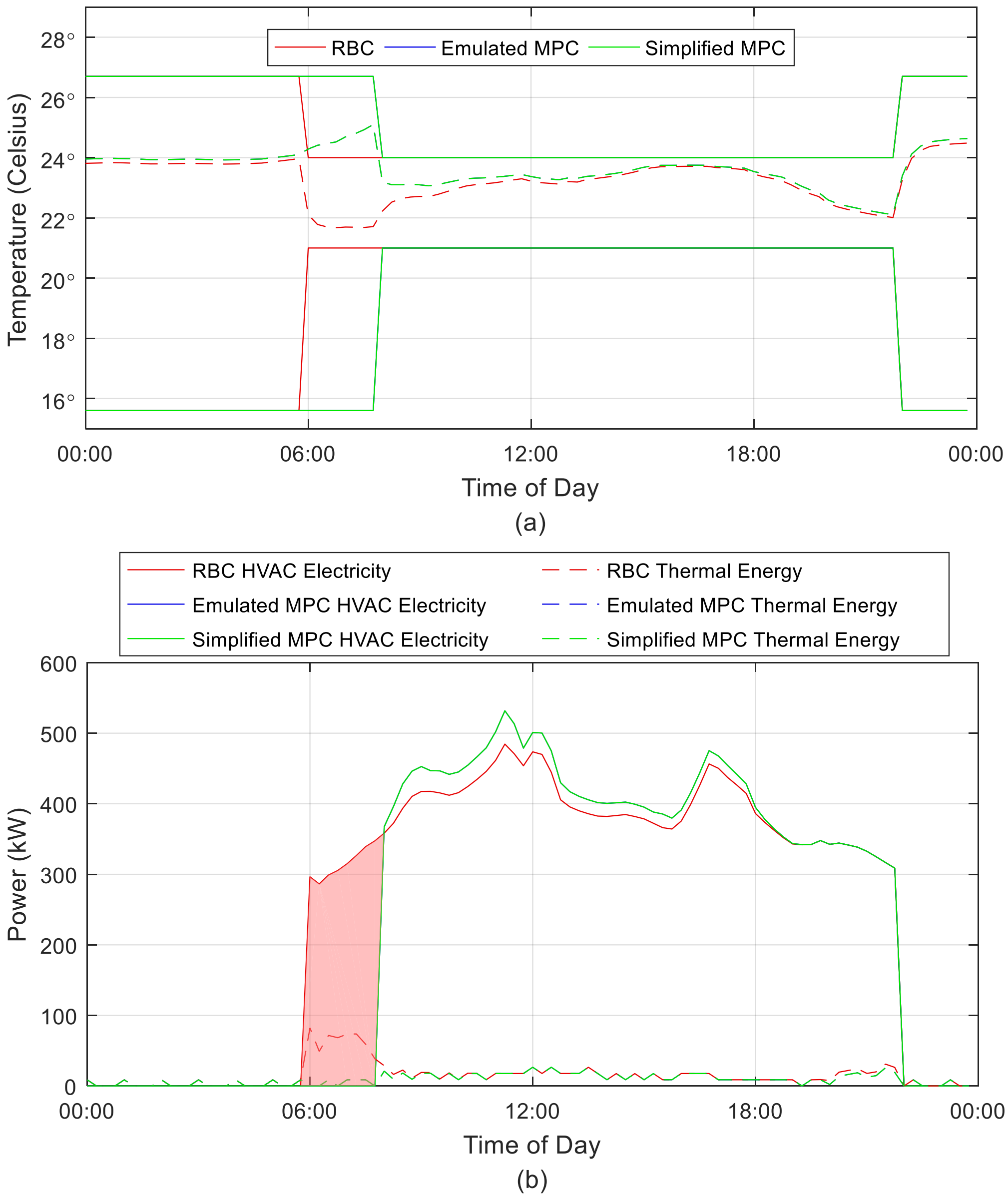


*Figure 10 New large office Halifax summer timestep analysis (a) Temperatures (setpoints are solid, temperature is dashed) and (b) Power*