Development of a remotely-sensed home energy labelling tool

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Abstract

There is an increasing market for home energy labelling and retrofit concierge services in Canada. The demand comes from individual homeowners looking for tailored advice to upgrade their home, to governments looking for effective ways to evaluate and improve their building stock. To achieve both objectives a remotely-sensed approach will be necessary to process the required number of homes at speed and at scale.

A retrofit concierge tool has been developed and deployed for a major Canadian city. The tool is underpinned by a grey-box model implemented in Python that provides energy consumption estimates for the existing home and a suite of proposed upgrades. The model is quick to run inside a web framework, allows for multiple model iterations to be performed simultaneously, and has been validated against HOT2000. The model is paired with a concierge service to offer homeowners cost-effective solutions to reduce their energy bills and carbon emissions.

Introduction

Home energy labelling has been identified as a tool to drive greater energy efficiency and decarbonization of Canadian single-family dwellings. Home energy labels assign a score or grade (ie. the label) to a home based on its modelled or measured energy consumption in either absolute terms, or relative to its peer buildings. Home energy labelling programs have been demonstrated to provide a number of benefits to participants (Kukadia et al., 2022). This includes energy cost savings, increased property values, and homeowners who are more informed about their home's performance and retrofitting options. Publicly shared benefits include improved code compliance, market transformation, consumer protection and job creation (Frappé-Sénéclauze et al., 2015).

The most common home energy labelling system in Canada is the EnerGuide Rating System (*NRCan*, 2015a). EnerGuide assessments are voluntary for homeowners who are interested in improving the energy-efficiency of their homes. Completion of an EnerGuide assessment was often part of the criteria for obtaining incentives from government energy efficiency programs.

The established assessment procedure is for a qualified energy assessor to perform an in-person evaluation of a home following the EnerGuide technical procedures (*NRCan*, 2015b). An EnerGuide assessment includes a blower door test, visual and tactile inspection of the home's building envelope and HVAC systems, which feeds into a HOT2000 energy model, which generates the EnerGuide score (GJ/a post 2015, 0-100 score relative to a reference building pre 2015). This HOT2000 model can be used to generate a list of recommended energy efficiency measures with associated savings for homeowners to consider. When applying for incentives, the results of the HOT2000 model get added to the EnerGuide database. This database contains EnerGuide scores, building locations, energy end-uses as well as key parameters input into those HOT2000 models.

While this established procedure has worked for a number of years, there are some limitations and opportunities for improvement when it comes to evaluating our existing building stock. Time and cost are the primary limitations.

It takes a not insignificant amount of time (~4 hours) for an advisor to complete an EnerGuide assessment. Though there has been an increase in the number of registered energy advisors in Canada, there aren't enough advisors available to address the full scope of the problem at hand, retrofitting the entire residential building stock. Estimates show that between 3 and 5% of Canada's residential building stock needs to be retrofit every year to meet 2050 emissions targets (Haley & Torrie, 2021; Kennedy & Frappé-Sénéclauze, 2021). Currently the retrofit rates are less than 1%/year for residential buildings (Haley & Torrie, 2021; Hermelink et al., 2019). Performing energy assessments helps identify appropriate measures for each home, but also identifies which buildings have the greatest scope for savings. It is assumed that every home should have an assessment performed before proceeding with a retrofit. In order to meet the 3 to 5%/year target, a faster way of assessing existing homes is required.

A casual online search showed that EnerGuide assessments currently cost upwards of $600 for a pre-retrofit evaluation. Though some programs allow these costs to be

recovered, the high costs present an economic barrier, especially for low-income homeowners, whose homes often have the greatest scope for energy savings (Cluett et al., 2016). A cheaper way of providing energy labels and retrofit advice is required.

To combat the time and cost barriers in obtaining a home energy label, the concept of remotely sensed home energy labels has been introduced. A remotely sensed evaluation does not require an energy assessor to visit the home and is instead determined using statistical or machine learning models. These models use a combination of geospatial data, housing data (eg. EnerGuide dataset, property tax data), energy metering, and behavioural economics to generate energy labels (Kukadia et al., 2022). Once the required data is obtained a label can be estimated quickly and if data can be sourced for an entire communities, then rapid evaluation of the entire stock becomes possible.

The information generated from a remotely-sensed evaluation needs to be communicated to homeowners and other stakeholders. A 2022 report found that one of top barriers to retrofit adoption was a lack of guidance for homeowners during the process (Glave & Woollard, 2022). Our current retrofit business model is an "atomized" or "go-it-alone" model. This model requires homeowners to research their options, conduct a cost benefit analysis, and arrange contractors, often without the prerequisite knowledge to make the optimal decisions (Brown, 2018). The report recommended the development of a retrofit concierge service for home electrification. This concept is similar to a "one-stop-shop" business model, where a homeowner can engage one business to help with general education, home diagnosis, determination of what measures to take, and ensuring that installation is successful (Glave & Woollard, 2022).

A home energy labelling tool was developed for the City of Saskatoon to help overcome these limitations. The objective of this tool was to provide EnerGuide-equivalent labels for all of the city's single-family dwellings and make that information available to homeowners through a web framework. The website provides homeowners with their estimated energy consumption, carbon emissions, and total energy costs. In addition, the website provides an online concierge service providing homeowners with bundles of retrofit measures with estimated operational energy, emissions, and cost savings as well a price estimate for those measures.

In this paper, the process for developing the home energy labelling tool is described. A grey-box model consisting of physics-based energy calculations was combined with a data-driven approach to determine home attributes. The model has been validated against HOT2000.

Methods

A grey-box model was developed to determine EnerGuide-equivalent scores. This grey-box model consists of two components: 1) the home energy model (HEM) which calculates the home's energy consumption, and 2) the attribute assigner model (AAM) which predicts key input parameters to the HEM based on data from the EnerGuide database for Saskatoon. An additional criteria was that the models needed to execute quickly to simulate a large number of possible retrofit combinations, and to be responsive to user input.

Home Energy Model (HEM)

The HEM's job is to estimate an EnerGuide-equivalent score given a set of input parameters, meaning that the HEM should produce the same annual energy consumption (GJ/a) as HOT2000 would given those same input parameters. Four approaches were considered for the home-energy model:

1. Use HOT2000 directly
2. Physics-based model inspired by HOT2000's methods
3. Surrogate model
4. Data-driven/machine learning approach based on the EnerGuide database

It was decided to go with the second approach inspired by HOT2000's methods. This approach has a number of advantages relative to the others. First it is auditable and explainable, so we can understand where the model is performing weak or strong compared to its reference, HOT2000. And second it is extensible, so new features can be added without needing to retrain. Running HOT2000 directly would have been ideal, as it would give accurate EnerGuide-equivalent scores, however it is too slow and unreliable to run at the speed required inside the web framework.

HOT2000 is an ASHRAE 140 validated energy modelling software targeted toward energy simulation of single family homes (ASHRAE, 2017; Parekh et al., 2018). The software has its origins in the relatively simple bin method which conducts monthly heat loss and energy consumption calculations. Though it uses this simple method as its basis, HOT2000 does utilize some more advanced physics models in its heat loss calculations (BASESIMP for sub-grade heat loss and AIM-2 model for infiltration, (Beausoleil-Morrison & Mitalas, 1997; Walker & Wilson, 1990)), and empirical models to determine internal and solar gains (Barakat & Sander, 1982, 1986). The relatively simplicity of HOT2000's methods means it would be feasible to emulate it in a Python script. HOT2000 runs a sequential algorithm where subsequent steps are dependent on the previous step. This was mimicked in the HEM which consists of several sub-models as illustrated in Figure 1. This sequential algorithm was coded up in Python using the Pandas library. The Pandas library takes advantage of vectorization, which allows for thousands of simulations to be performed simultaneously, addressing a key design objective.

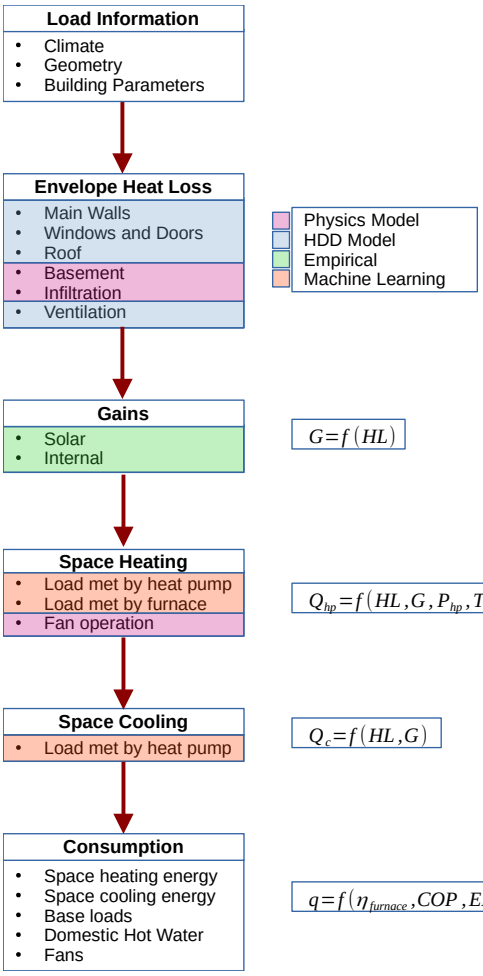

Figure 1: Sequential algorithm of the home energy model. The model uses a combination of simple HDD calculations (blue), physics-based models (pink), previously developed empirical models (green), and machine learned regression models (orange). Some stages are a function of previous steps.

A single-zone model was chosen for simplicity. All calculations are done on a monthly basis, using the weather data provided with HOT2000. EnerGuide default parameters were used for occupancy, lighting, hot water usage, setpoints, etc. Plan geometry was assumed to be rectangular (no re-entrant corners) with one or two above ground storeys. The length, width, and height of the building above and below grade are adjustable, as is the window to wall ratio (WWR). No overhangs or shading devices were modelled for simplicity. Thermal resistances, infiltration and ventilation rates, and the efficiencies of HVAC equipment are adjustable too.

The HEM's sub-models were validated against HOT2000 during development. To aide validation, a number of batch HOT2000 datasets were created with variation in the parameters of interest while keeping other parameters fixed. For example R-value, floor area, window sizes, etc, may be varied to determine solar gains, while keeping mechanical system parameters fixed. The sub-models were validated by comparing the sub-model's results to HOT2000's monthly outputs.

Because HOT2000 uses a bin method approach, the monthly heat loss (q) through many of the envelope components (c) can be calculated using a heating degree-day HDD approach with a monthly reference temperature (T_{ref}) of 20°C (the average heating setpoint under EnerGuide criteria).

$$q_c = \frac{A_c \cdot HDD_{20}}{R_c} \quad (1)$$

Equation 1 tended to work very well in winter months, but poorly in shoulder seasons. To improve the estimated heat loss, an effective HDD (HDD_{eff}) was determined for each month using a simple linear regressions as given in equation 2 and 3. These were based on generated HOT2000 datasets. For the above-grade walls only the monthly HDD and CDD were required to obtain $R^2 > 0.99$ between the HEM and HOT2000 heat losses. For the ceiling, additional terms were required including the R-value of the ceiling (R_{ceil}), monthly global horizontal solar radiation (I_{global}), and a constant (η). This is because the attic zone is modelled separately in HOT2000.

$$HDD_{eff} = \alpha\, HDD_{20} + \beta\, CDD_{20} \quad (2)$$

$$HDD_{eff,ceil} = \alpha\, HDD_{20} + \beta\, CDD_{20} + \gamma\, R_{ceil} + \delta\, I_{global} + \eta \quad (3)$$

It is not possible to estimate HOT2000's heat loss from infiltration and the basement using the HDD approach. For infiltration, the AIM-2 model was implemented in Python. The AIM-2 model calculates the infiltration rate as a function of house geometry, interior and exterior temperatures, and wind speed.

For the basement heat loss, the BASESIMP model was implemented into Python. The BASESIMP model is a regression analysis built atop of a number of two-dimensional finite-element simulations. A series of coefficients were found that can estimate the heat loss for a number of foundation types (full basement and slabs-on-grade) and insulation arrangements (full exterior or interior, partial wall, perimeter slab, uninsulated, etc). Coefficients for the BASESIMP model were found in the ESP-r source code (*ESP-r*, 2022). The BASESIMP calculation is a function of:

- basement type;
- basement geometry;
- R-value of insulation;
- arrangement of insulation;
- monthly ground temperature and soil properties

HOT2000 uses an empirical formula to determine the monthly "useful" internal and solar gains. These are subtracted from the monthly heat losses calculated in the

previous step to determine the monthly heating load. Barakat and Sander (1986) provide equations to determine the useful internal gains, but these do not always match the HOT2000 outputs in the summer and shoulder seasons. Using the HOT2000 dataset an alternate equation was determined as a function of above-grade heat losses.

Determination of useful solar gains was trickier. Barakat and Sander (1982) published isopleths graphs to determine the fraction of solar gains which are useful (η_s). η_s is a function of what are called the Gain-load ratio (GLR), Mass-gain ratio (MGR), and a variable called the allowable rise which is the number of degrees the temperature is allowed to rise above the heating setpoint before cooling actions are taken. Higher allowable rises allow for more thermal storage and higher useful gains. The equations used to determine η_s are not published. Equations for the isopleths were reverse-engineered with the help of a generated dataset. The isopleths are a sigmoid or logistic shape and regular linear regression techniques did not produce adequate results. The best results were obtained by filtering monthly values from the dataset where the MGR = 1.0, 2.6, and 7.2 ± 0.1 (the values used in the paper) and determining the equation of best fit (Figure 2). An equation in the form of the sum of two logistic curves (with coefficients k, x_0, and n)was able to recreate the isopleths with linear interpolation used to calculate η_s for intermediate values of MGR.

$$\eta_s = \frac{0.5}{\left(1+e^{k_0(GLR-x_0)}\right)^n} + \frac{0.5}{\left(1+e^{k_1(GLR-x_0)}\right)^n} \quad (4)$$

The fraction of useful gains was then multiplied by the incident solar radiation entering through all windows to determine the monthly useful solar gains (G_s). $I_{direction}$ is provided in the weather files for eight window orientations.

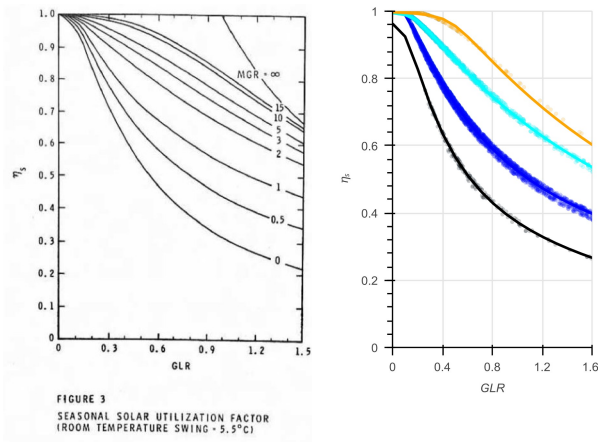

Figure 2: Useful solar gain isopleths. Original Barakat and Sander curves (left) and recreated curves using Equation 4 (right).

$$G_s = \eta_s \cdot \sum_{i=n_{windows}} I_{direction,i} \cdot A_i \cdot SHGC_i \quad (5)$$

With the useful internal and solar gains determined, the auxiliary space heating demand can be calculated by subtracting the gains from the envelope heat loss.

$$q_{spaceHeating} = q_{envelope} - G_{solar} - G_{internal} \quad (6)$$

In the HEM, only gas furnaces and heat pumps are considered for space heating. Gas furnaces are the dominant space heating method in Saskatoon, and heat pumps are the proposed decarbonization retrofit solution. In Saskatoon temperatures often dip below a heat pump's cutoff temperature (-22°C) where it can no longer operate. Therefore, homes with heat pumps need a backup heating system to handle the heating demand on cold days. In the HEM the backup system is assumed to be a gas furnace.

For homes with a heat pumps, it is necessary to know what percentage of the monthly heating load is met by the heat pump and what percentage is met by the backup system. The percentage was determined using a HOT2000 dataset with homes of varying sizes, infiltration rates, and R-values to obtain different heating loads, and varying heat pump capacities and COPs. A known limitation of HOT2000 is its inability to simulate cold-climate air-source heat pumps (CCASHP) properly because it uses default performance and capacity curves which do not match those of CCASHPs. To get around this NRCan has developed a tool which can convert a CCASHP manufacturer's rated specs into equivalent rated COP and capacity using the default curves and will give equivalent results in HOT2000 (*NRCan*, 2023).

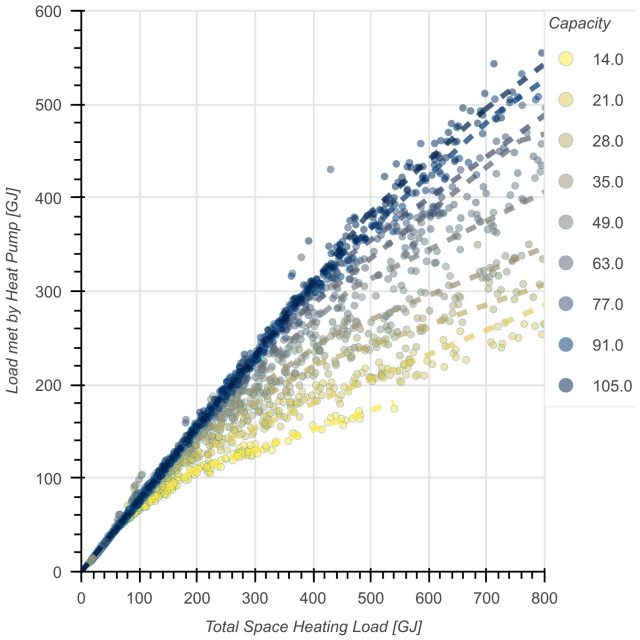

Figure 3: Heating load met by the heat pump by its capacity

Equations to calculate the load met by the heat pump were found for discrete heat pump capacities as a function of the total space heating load (Figure 3). For heat pumps that are adequately sized, the load met by the heat pump was nearly a linear function of the space heating load (≈76%).

There is no online documentation on how HOT2000 calculates space cooling energy and the outputs file only contain annual cooling energy. There is no monthly demand or consumption to help determine and verify the calculation procedure. As a result it was decided to use a linear regression model to calculate space cooling energy. This model uses previously calculated inputs (annual heat loss), geometric properties (window area per orientation, floor area, and house volume), infiltration and ventilation rates, and mechanical parameters (HRV efficiency, heat pump COP).

With the loads for all end-uses known it is then possible to determine the annual fuel consumption and emissions. These are straightforward calculations apart from the energy consumed by the heat pump, where the annual effective COP is needed. Using the dataset generated for heat pump loads, the effective COP was a piecewise linear function of the space heating load [MJ] divided by the heat pump's rated capacity [kW] (Figure 4). Gas consumption was calculated using the furnace's efficiency, and DHW energy factor. Other electrical end-uses such as lighting, and appliance energy were calculated using EnerGuide defaults.

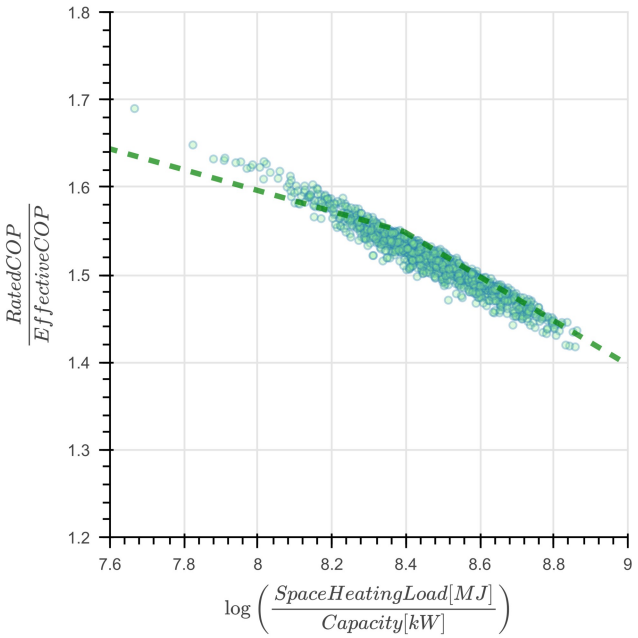

Figure 4: Effective COP versus space heating load over heat pump capacity.

Attribute Assigner Model (AAM)

The AAM produces key input parameters for the HEM (eg. infiltration rate, R-value, window type, etc). These were based on the EnerGuide dataset and property database obtained from the City of Saskatoon. The AAM determines these parameters based on Forward Sortation Area (FSA), year-built and floor area – items which are common to both the EnerGuide database and property database. This follows an assumption that buildings from the same neighbourhood and timeframe will have been built using comparable materials, HVAC systems, and techniques. Parameters for each FSA were binned by decade built.

The parameters determined by the AAM are default assumptions presented to users through the web interface. To improve the results, a questionnaire is presented to users to improve upon the default parameters assumed. Users are asked if the have made any upgrades related to their home regarding airtightness, windows, insulation, and space and water heating system.

Once the default assumptions have been updated an array of energy efficiency bundles are created and simulated using the HEM. Selected results are then presented to the user that present the estimated improvement in the EnerGuide-equivalent score, annual energy cost savings, and predicted payback period of those measures.

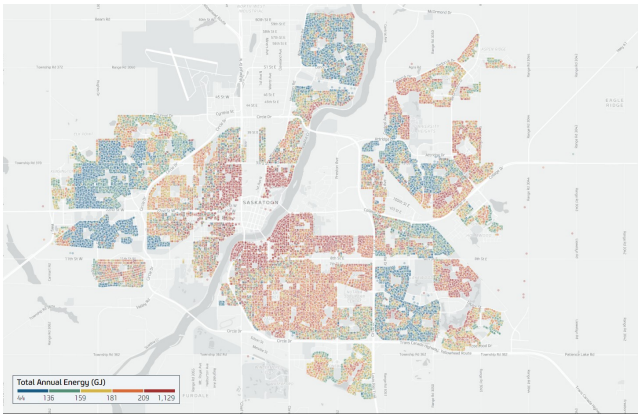

Figure 5: Map of the predicted energy consumption of single-family homes in Saskatoon (Open Technologies, 2023)

Results

The HEM was validated against HOT2000 for the city of Saskatoon. A batch of 25000 HOT2000 simulations were created and run with varied parameters so that the dataset was representative of Saskatoon's single-family homes building stock. The EnerGuide database was used to determine the ranges for several of these parameters. These include building footprint, wall, ceiling, and basement insulation, air infiltration rate, furnace, HRV, and DHW efficiency, window type, and basement type. The values for these parameters were chosen from a Gaussian or skewed distribution (eg. air infiltration rate), or from a weighted choice model (eg. basement and window types). Some parameters are not available in the EnerGuide database (eg. WWR). Here a uniform distribution within reasonable limits was used. Other parameters, such as

Table 1: Relative and absolute errors of the HEM compared to HOT2000 outputs

	Relative Errors						Absolute Errors				
Metric	**Mean**	**< 1%**	**<2.5%**	**< 5%**	**< 10%**	**< 15%**	**Mean**	**< 1 GJ**	**< 5 GJ**	**< 10 GJ**	**< 25 GJ**
Annual Electric Consumption	1.63%	25.8%	60.9%	93.0%	99.9%	100.0%	0.990	55.90%	96.26%	99.72%	100.00%
Annual Gas Consumption	-0.44%	25.4%	57.0%	85.5%	99.4%	100.0%	-0.327	30.52%	85.51%	98.10%	100.00%
Annual Total Energy Consumption	0.44%	33.6%	71.0%	94.6%	100.0%	100.0%	0.662	23.53%	81.04%	97.14%	100.00%

whether a building had a furnace or a heat pump were evenly split for testing purposes. The annual results from each HOT2000 file were collected and compared to the HEM results.

The results of the HEM relative to HOT2000 annual fuel consumption outputs are presented in Table 1. The most critical metric is the Annual Total Energy Consumption which is equivalent to the EnerGuide score. Overall the HEM performed within our expectations. It was able to predict 94.6% of EnerGuide scores with less than 5% relative error and all EnerGuide scores within 10% relative error. The magnitude of errors were normally distributed with a minor tendency to overpredict energy consumption, as seen in Figure 6. In terms of absolute error, 81% of simulations were within 5 GJ of the EnerGuide score. Absolute errors scale with the size of the home modelled. The buildings with large absolute errors tended to be the largest homes.

The accuracy of the sub-models relative to HOT2000 outputs were also noted, as shown in Table 2. The best performing sub-models were for the above-grade building envelope heat loss – with all simulations having less than 5% relative error. The worst performing sub-models were for the basement and ventilation/infiltration. This is interesting because these are the only two complex physics-based models being implemented. Our implementation of the BASESIMP model tended to overpredict heat losses, sometimes with large errors (>15%). It was observed that the greatest losses occurred when basement insulation was low. The implementation of the AIM-2 model tended to underpredict the infiltration heat loss. This was the result of consistent bias in absolute error that translated into larger relative errors. Notwithstanding, the poor performance of the basement and infiltration sub-models, the total envelope heat loss had low relative errors with all simulations having less than 10% error.

Table 2: Relative errors of HEM sub-models

Metric	**Mean**	**< 1%**	**<2.5%**	**< 5%**	**< 10%**	**< 15%**
Ceiling	-1.9%	20.4%	57.7%	96.7%	100.0%	100.0%
Main Walls	0.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Windows	0.3%	100.0%	100.0%	100.0%	100.0%	100.0%
Above-grade Envelope	0.0%	98.7%	99.9%	100.0%	100.0%	100.0%
Basement	3.7%	8.9%	25.9%	53.7%	75.9%	85.0%
Infiltration &Ventilation	-9.0%	0.1%	0.2%	8.5%	68.8%	93.2%
Total Envelopes	-0.5%	28.6%	72.1%	96.1%	100.0%	100.0%
Internal Gains	1.8%	14.8%	33.3%	54.0%	75.4%	88.0%
Solar Gains	2.4%	14.3%	34.3%	60.2%	85.8%	96.1%
Total Gains	1.6%	25.2%	54.7%	77.1%	96.5%	100.0%
Thermal Demand	-1.5%	19.0%	46.1%	79.3%	98.3%	99.9%
Load Met by Heat Pump	-1.1%	18.4%	42.6%	72.8%	96.5%	99.9%
DHW Energy	-0.5%	85.1%	100.0%	100.0%	100.0%	100.0%
Cooling Energy	4.4%	8.7%	20.6%	39.3%	69.0%	86.1%

The gains sub-model is dependent on the envelope heat loss so any relative errors from the envelope sub-model carry through in the calculation. This can complicate validation of the sub-model to HOT2000 outputs. These sub-models tend to overpredict the gains.

Combining the envelope heat loss and the gains sub-models results in the home's thermal demand. This is important metric to get right as it is the basis for mechanical system and fuel consumption calculations. Here the HEM performed well, with 98.3% of simulations having a relative error of <10%. Of the simulations with

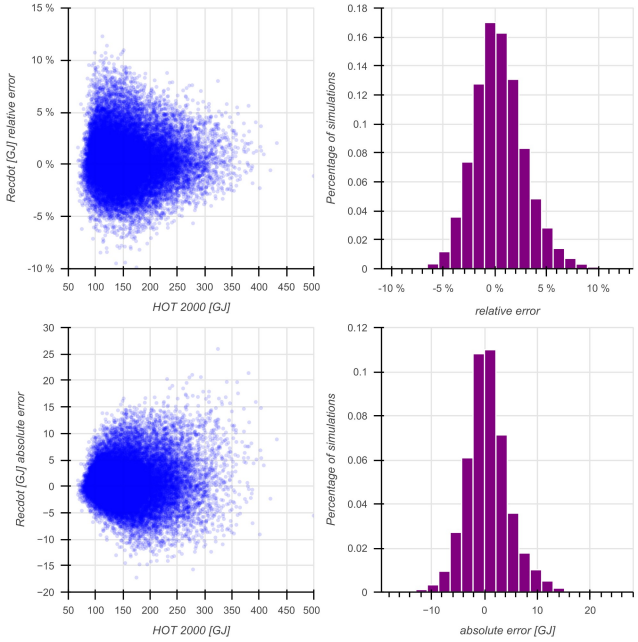

Figure 6: Annual energy consumption relative errors (top), absolute errors (below)

poor relative error, they tended to be smaller buildings with better envelopes and absolute errors that were considered acceptable (<5 GJ).

In simulations with a heat pump, we were able to predict the load met by the heat pump and furnace with good accuracy. This comes with the caveat that any errors from previous steps carry over, and mask the validity of this model relative to HOT2000 outputs. Cooling energy, which was calculated using a machine learned model, performed poorly compared to other sub-models in terms of relative error. However this often translated to only minor absolute errors because space cooling energy is not substantial compared to space heating energy in Saskatoon.

Discussion

Although the model performed within our initial expectations, there is still room for improvement. First is the relatively poor performance of the BASESIMP and AIM-2 models implemented in the HEM. The issues with these models originated with the lack of documentation of HOT2000's source code. Despite having the BASESIMP coefficients, other inputs are uncertain, namely monthly ground temperatures and soil properties. It was not possible to reverse-engineer these uncertain parameters that worked for all basement types. It could also be that HOT2000's implementation has been simplified or enhanced in ways which were not understood or documented. Another example of where the lack of documentation hurt was when calculating solar gains. It was discovered late in the project that HOT2000 appears to treat window types (picture, sliding, patio door) differently to one another. During development of the solar gains sub-model all window types were considered, and a consistent error was observed and a minor correction applied universally to the incoming solar radiation. Retrospectively, this was misleadingly applied and accounts for some of the error observed in Table 2. Having documentation to help us confirm how HOT2000 works versus how we think it works would of helped to avoid these problems.

For the HEM, we actually simplified HOT2000's bin method calculation, avoiding the step of distribution into temperature bins, and repeating calculations at different outdoor temperatures. By adopting more of the bin method approach we could solve some of the inaccuracy of the AIM-2 model and our model to determine the loads met by the heat pumps and furnace at finer intervals. This would not come at the expense of significant computational time.

Another necessary area of improvement is making the HEM applicable to all Canadian climates. Currently it is only valid for Saskatoon. The original intent was to have the HEM applicable to all climates, but the issues with BASESIMP, AIM-2 and solar gains led us to focus on just Saskatoon under the time constraints. The HEM can be validated for other cities following a similar methodology (while addressing some of the deficiencies). There are future plans to compare the HEM and HOT2000 with equivalent EnergyPlus simulations and with EnergyPlus surrogate models of single-family homes.

HOT2000 and the HEM can be considered to be a "medium-complexity" physics based energy modelling tool, meaning that it is more complex than the ISO EN 52016 (2017) or bin method approaches, and less complex than contemporary tools such as EnergyPlus, IES-VE, or ESP-r. These "medium-complexity" models attempt to balance the speed of simple models with the fidelity and accuracy of complex models, but don't excel at either. Current research trends are towards either complex data-driven energy modelling tools (eg. surrogate models) and simpler physics-based and data driven models for rapid modelling of the building stock. This begs the question of what is a purpose of these medium-complexity models moving forward?

The HEM could serve as an enhanced foundation for building stock models, especially those which have an evolutionary element such as agent-based models because retrofit measures can be evaluated and applied.

A future improvement of the HEM would be to wrap it as a physics-informed neural network (PINN). The HEM would serve as the basis of the PINN calculating base demands and a neural network would handle the epistemic uncertainty. The PINN would be an alternative method for determining the internal and solar gains, the basement heat losses, and effective COPs, as done in the HEM. The PINN could be trained on batches of HOT2000 simulations, EnergyPlus simulations, or measured data depending on application. This would combine the speed and extensibility advantages of the HEM with the greater modelling and output reporting detail offered by EnergyPlus, and allow for additional metrics (such as overheating) not covered by HOT2000, ISO EN 52016 and many other data-driven models to be captured.

Conclusion

The increasing demand for remotely-sensed home energy labelling for single-family homes led to the creation of a grey-box modelling tool for the city of Saskatoon. This home energy model was calibrated to produce EnerGuide-equivalent scores following calculation procedures similar to those of HOT2000. The HEM consists of several sub-models which uses a combination of degree day calculations, physics-based models, and linear regression models trained on batches of HOT2000 simulations. The HEM was able to predict an EnerGuide-equivalent score within a relative error of 10% in all circumstances and within a 5% relative error 94.6% of the time. The HEM was strongest at predicting above-grade envelope heat and weakest at predicting basement heat losses and solar gains. The HEM is paired with Attribute Assigner Model to predict key parameters of houses in Saskatoon. Residents

are able to access their predicted EnerGuide-equivalent scores through a website.

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