Analysis of Feature Importance in Modeling Ground Source Heat Pump Systems Using Broad Parametric Analysis, Load Characterization and Artificial Neural Networks

David Rulff[1], Kevin Cant[1], Theo Christiaanse[1], Ralph Evins[1]
[1]Energy in Cities group, Department of Civil Engineering, University of Victoria, Canada

Abstract

This paper considers the case of modeling a ground source heat pump with a range of temporal load dynamics to identify the important features used for estimating performance. Heating and cooling load profiles are generated using extensive parametric sampling of a base office building simulation, including variation of a set of parameters for heat pump system design and properties of the ground. Load characteristics are extracted from the models using aggregate output and application of Fourier Transform decomposition to describe periodic behaviour. Artificial neural networks are used to estimate the heating and cooling performance metrics of the ground source heat pump system, with significant accuracy using the full feature set (R^2>0.98). The resulting loss in accuracy due to reduced dimensionality through feature grouping is also shown, with implications for early stage design and performance modeling.

Introduction

Ground Source Heat Pump systems have the potential to significant reduce building-sourced GHG emissions by efficiently exchanging thermal energy with a Ground Heat Exchanger (GHE) and using electricity as a low-carbon energy input where generation comes from renewable sources.

The significant variability in weather and ground conditions, along with the large number of design parameters for both the building systems and GHE field, creates a vast problem space that makes simulation of explicit configurations highly complex and generalized modeling efforts computationally intractable (Raymond, 2018). Additionally, the detailed information required to accurately model the GSHP system is not typically available at the early stages of design.

The objectives of this study are:

1. separate the overall problem into component submodels (building, GSHP, GHE) and reduce dimensionality of the problem space through aggregate characterization of building heating and cooling load profiles to support generalization of results
2. identify the important features of the systems that influence GSHP performance and loading ratios through application of large scale parametric simulations
3. provide and compare the accuracy of preliminary models based on simplified feature groupings for prediction of GSHP performance using Artificial Neural Networks (ANN)

Existing Work and Contribution

The level of detail Incorporated into the model of thermal energy transfer and storage dynamics for GHE fields varies depending on the purpose of the work. Reviews of the research domain distinguish between thermal response factor methods, numerical thermal methods, artificial neural network models, and state-space models (Atam and Helsen, 2016).

The behaviour of a GHE field as a thermal mass can be measured through the response over time to unit step heat pulses (Li and Lai, 2015). A major development by Eskilson (Eskilson, 1987) used a numerical finite-difference method to express the temperature response at the borehole wall in terms of dimensionless "g-functions". These g-functions must be calculated directly for each GHE configuration, which can be computationally time-consuming for parametric studies (Yang et al., 2010). This work has since been expanded upon in a variety of ways (Bertagnolio et al., 2012), though g-functions continue to be used in integrated building simulation software (Florides and Kalogirou, 2007).

Work on characterizing ground temperature profiles (both surface and at various depths) based on local weather information and material properties is an ongoing area of research (Badache et al., 2016), including identifying relationships between air temperature, ground temperature and altitude (Signorelli and Kohl, 2004) or investigating the impact of surface air temp fluctuations on long term vertical GHE performance (Bidarmaghz et al., 2016).

Significant headway has been made with the application of machine learning to GHE modeling, due to the complexities inherent in the problem (Zhou et al., 2019). Artificial Neural Networks (ANN) have shown promise for capturing the important dynamics of the GHE field (Park et al., 2018)(Zhou et al., 2019).

ANNs are used heavily for both classification and regression, and with sufficient training data can accurately predict building energy outputs, such as annual heating and cooling loads and heat pump seasonal COPs, given proper hyperparameter tuning (Westermann and Evins, 2019). This study adopts ANN methods to support sensitivity analysis, feature selection and to develop computationally efficient representations of not just the GHE field, but also the GSHP plant performance in response to variable thermal load profiles.

There has been some research into applying the Fast Fourier Transform to decompose load profiles into characteristic frequencies, with uses including forecasting of electrical consumption (González-Romera et al., 2008) and for characterizing heating demands to inform the design and sizing of thermal storage (Pinnau and Breitkopf, 2015). This paper extends this analysis with the use of Fourier Transform to identify important periodic features of heating and cooling profiles influencing GSHP performance.

The design of GSHP systems has a strong tradition in engineering practice, with ASHRAE publishing a detailed design guide (Kavanaugh and Rafferty, 2014)(Ahmadfard and Bernier, 2018). Vital considerations for design include avoiding seasonal drift in ground temperatures due to unbalanced heating and cooling loads, which largely drives the need for accurate, detailed simulation of GHE fields (Self et al., 2013). Research into the performance of heat pump technology itself continues (Chua et al., 2010); however, the fundamental physics of the vapour compression cycle are well understood, and performance can be reliably estimated with a reduced set of system variables including fluid temperatures, flow rates and equipment design specifications (noa, 2001).

EnergyPlus is a whole building simulation program that integrates Eskilson's g-functions to model vertical GHE fields connected to GSHP plants in a variable time-step load aggregation scheme, showing average error in predictions for heat transfer of 4-6%, and for electricity consumption of less than 3%, compared to experimental data (Fisher et al., 2006). There exists significant potential to leverage the detailed, building-integrated simulation potential of EnergyPlus for broad parametric studies of GSHP performance potential (Kang and Cho, 2016)(Padhmanabhan, 2005).

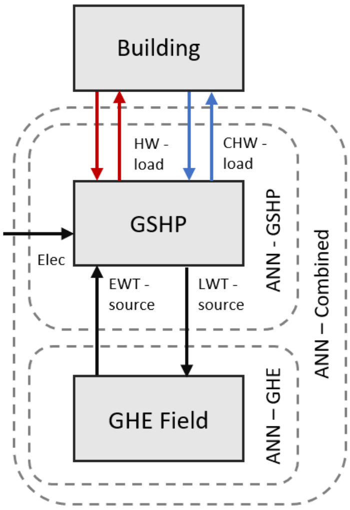

Figure 1: Model Overview.

Methodology

Model Structure

The overall problem space was divided into three component sub-models for analysis (shown in 1): the building, the GHE field, and the GSHP plant. The building sub-model encompasses an expansive set of architectural, mechanical and electrical design parameters that are used in an hourly simulation to generate heating and cooling loads. The GHE field is represented by parameters about ground conditions and interactions with the geo-exchange system configurations, capturing dynamic heat transfer and storage behaviour in the simulation. The GSHP plant connects the building loads to the GHE field, accounting for input equipment specifications and controls to determine the electricity consumption required to handle the heating and cooling loads of the system.

All components are simulated in EnergyPlus using BESOS for access to parametric modeling and machine learning functionality, over the course of one operating year for Victoria, BC (using standard Canadian Weather for Energy Calculations (CWEC) provided by Environment Canada).

Building Definition

Baseline building assumptions were derived from the National Energy Code for Buildings (2015), with general inputs for building program, operating schedules, and geometry generated through work by National Resources Canada (NRCan) versions of the Commercial Prototype Building Models originally created by the US DOE Canmet-Energy (2019). A Medium Office archetype was selected as a common platform for generating thermal load profiles and exploring the impact of a variety of system changes.

Each rectangular floorplate is 1,660 m^2 and represented by 5 thermal zones in the model (perimeter

	Parameter	units	range
1.	Orientation	deg	(-45) - 45
2.	Wall/Roof Insulation	W/m^2K	0.7 - 3.0
3.	Slab Thickness	m	0.01 - 0.10
4.	Window U-value	W/m^2K	1.0 - 2.5
5.	Solar Heat Gain Coef.		0.2 - 0.8
6.	Window to Wall Ratio	%	20 - 90
7.	Horiz. Shading Depth	m	0 - 1
8.	Daylight Control	frac	0 - 100
9.	Lighting Power Density	W/m	3 - 15
10.	Plug Load Density	W/m	0 - 20
11.	Data Centre Load	kW	0 - 10
12.	DHW Load	L/s	0.04 - 0.2
13.	Infiltration	L/sm^2	0.1 - 0.5
14.	Ventilation Effectiveness	frac	0.5 - 1.5
15.	Cooling Setpoint	°C	22 - 26
16.	Humidification	RH	0 - 40
17.	Dehumidification	RH	50 - 100
18.	Peak Occupancy	m$^2/occ$	10 - 100
19.	Storeys		3 - 7

Table 1: List of building design parameters for Medium Office

and core). A central VAV system with air-side economizer control and heat recovery serves each zone, with hydronic reheat coils and baseboards for perimeter heating loads. An additional server room is included with each building, acting as the space containing the additional IT loads and served by a fan coil unit connected to the central hydronic loops. To generate a sufficiently diverse set of heating and cooling loads, variations of a set of building design parameters was included as part of the expansive sampling of the problem space. These parameters, along with their sampled ranges, are shown in Table 1.

Geo-exchange Field

This study focuses on a vertical, closed loop, ground-coupled heat exchanger configuration, which make up 80% of installed systems in Canada (Raymond, 2018). The field is comprised of vertical boreholes drilled into the ground with closed piping loops and grout infill, conveying the heat transfer fluid and facilitating exchange to the surrounding soil, rock and other subsurface materials.

The parameters representing the properties of the ground are included in Table 2, along with borehole design context assumptions (Lambert, 2013). Boreholes drilled between 75 to 250m may pass through

	Parameter	units	range
20.	Ground Conductivity	W/mK	0.5 - 8.0
21.	Soil Specific Heat	J/kgK	calc'd
22.	Average Soil Surface Temp.	°C	8 - 22
23.	Average Amplitude of Temp.	°C	2 - 12
24.	Borehole Spacing	m	5 - 8
25.	Borehole Length	m	75 - 200
26.	Number of Boreholes		calc'd
27.	Ref. Field Loop Flow	m$^3/s$	calc'd

Table 2: List of design parameters for the GHE field

	Parameter	units	range
28.	Cooling Capacity	kW	10-200
29.	Cooling Design COP		6.2
30.	Heating Capacity	kW	calc'd
31.	Heating Design COP		3.6
32.	Flow Rates	m$^3/s$	calc'd
33.	Pump Power	W	calc'd

Table 3: List of GSHP design parameters for Medium Office

organic sand and soils, silt and clay deposits, limestone, granite and other dense rock; therefore, ranges in properties were selected accordingly (Raymond, 2018).

Ground Source Heat Pump Plant

All heating and cooling loops are connected to a central plant comprised of a multi-compressor GSHP, along with supplemental chillers and boilers. The GSHP takes priority for satisfying building heating and cooling loads, with peaking equipment scheduled to operate in sequence. Both building-side loop and ground loop connections control energy transfer using 3-way bypass flow-control valves.

The heat pump performance is calculated using EnergyPlus multi-linear regression curves that determine part load thermal output and power consumption. The coefficients assumed were typical values used in the program's sample files and described in the engineer's manual Kavanaugh and Rafferty (2014).

The GSHP parameters are listed in Table 3, with the primary independent variable being reference cooling capacity. Reference heating capacity is set to be equal to nominal cooling capacity, and flow rates through the equipment and GHE is set based on a design loop temperature difference across the heat pump. Rated COP values are adjusted to ASHRAE 90.1 testing conditions Kavanaugh and Rafferty (2014).

Parameter Sampling

The overall parametric run involved 10,000 simulation samples using latin-hypercube sampling, which divides the design parameter space into equally large hypercubes and randomly collects samples from within each hypercube. Hourly data for each of the variables was extracted and stored for each EnergyPlus sample. These were used to calculate the hourly building thermal loads, heat pump output, loop temperatures, and electricity consumption by the equipment to satisfy heating loads and cooling loads.

Model Characteristics and Feature Selection

Characterizing the heating and cooling load profiles across samples is important both to understand the bounds of the scope of this study, and to narrow in on the significant information that influences GSHP performance. A set of profile characteristics have been selected to encompass the high level information that might be available to practitioners estimating GSHP performance, along with metrics capturing profile ranges and temporal dynamics. This set is not intended to represent an exhaustive collection, and future study could incorporate more granular characteristics (such as total monthly loads).

The Detailed Building Characteristics include seven derived from FFT decomposition of the hourly net heating and cooling load profiles. Each of these characteristics represents the cumulative amplitude of distinct, meaningful "bins" in the frequency domain. "Imbalance" represents correlation with a zero frequency component, therefore showing annual imbalance between heating and cooling. Stronger amplitude in each of the other bins reflects greater contribution to total loads from periodic behaviour of the noted frequency. These features help characterize the relationships between base thermal demands, periodic loading and "noise" for each run.

Overall, these characteristics form the input parameters that will be considered to define the building loads independent of the detailed building information, operation, and weather that lead to the generation of these characteristics. Converting to these characteristics allows for agnostic comparison of GSHP performance regardless of building details, and allows for generalization of the results. The results apply for buildings with load characteristics within the bounds of this study. The original building parameters were important only for generating the heating and cooling load profiles, and are therefore considered extraneous to the following stages of the study.

Feature Importance Selection

The four primary output objectives for the models in this study are the proportion of annual load satisfied by the GSHP (proportion of load met) and the relative electrical input to satisfy those loads (seasonal COP, or SCOP) for each of heating and cooling, which are identified as the four 'labels'. Artificial Neural Networks (ANNs) are used to determine feature importance, and the accuracy of the ANNs depending on the selection of input features represent the relative accuracy of simplified inputs to the energy model.

Hyperparameter tuning of ANNs is the selection of inputs and architecture that defines the ANN model, such as regularization coefficient, number of nodes per hidden layer, and total number of hidden layers. In order to compare the performance of the ANN models, the overall parametric simulation dataset is split first into a training set (with 80% of total simulations), and a testing set (with 20% of total simulations). The training set is further divided using the k-folds cross validation method with three folds. Hyperparameter tuning was performed for a baseline ANN that included the entire feature set and output all four labels. The optimal hyperparameters were retained and held consistent across all subsequent ANN models in the study.

The main metric used for scoring of the models was the coefficient of determination (R^2 score). An ANN generated by all of the features is used as the baseline model. Feature importance was first estimated by removing one feature at a time and retraining the model. The average score of the new model across the four labels was compared to that of the baseline model with all features. The difference in scores was used as the metric for comparable feature importance. A larger difference in scores implied that there was a larger dependence on that feature, or that the feature was more important. However, the presence of correlated features would artificially reduce the importance metric; where if both features are removed the overall loss in score would be greater than the sum of the two individual reductions.

Simplified Feature Grouping

The overall feature space is grouped into different sets of simplified features. These feature sets are grouped to represent different levels of information that may be available to the designs and modellers at early stages. The key characteristics and feature groupings are summarized below:

1. Simple Building Information, including
   - Site Location
   - Total Annual Heating Load
   - Total Annual Cooling Load
   - Relative Heating HP Sizing
   - Relative Cooling HP Sizing
2. Detailed Building Characteristics, including
   - Simple Building Information

- Imbalance
- Annual
- Semiannual
- Weekly
- Daily
- Semidaily
- Hourly

3. Detailed Soil Conditions, including
   - Detailed Building Characteristics
   - Ground Thermal Conductivity
   - Ground Thermal Heat Capacity
   - Average Amplitude of Surface Temperature
4. Site Location, including
   - Average Soil Surface Temperature

Results

Load Characterization

Three illustrative buildings are selected based on building designs with the 90^{th}, 50^{th} and 10^{th} percentiles for annual heating demand. Figures 2 shows the heating and cooling, along with the corresponding temperature of the flow leaving the GHE field. Some general observations can be made, such as that the outlet temperature becomes more volatile under greater cooling loads, and the field is generally warmer. However, these examples also show that even in the same location, for the same building type, total heating and cooling loads are not always correlated.

Figure 3 summarizes the performance under each building characteristic for the full sample set (of 9440 building configurations), with the three buildings highlighted.

Feature Importance

The baseline model hypertuning resulted in an optimal model with an overall R^2 score of 0.99 on the testing set, with individual label scores shown in Figure 5. The optimal hyperparameters identified by the k-folds cross-validation procedure included two hidden layers each with 105 nodes, and an L2-regularization coefficient of 1.0. These hyperparameters were included for all future ANN development. Additional models are developed to identify the feature importance. The results are shown in Figure 4 for each label. The average ground surface temperature dominated the feature importance for both heating and cooling COP. Almost all other features had a negligible impact on R^2 score. Feature importance was more widespread for proportion of heating and cooling load satisfied by the GSHP.

Reduction of Features Accuracy

From the initial full feature baseline ANN model, three additional models were trained with subsets of features based on the original characteristic sets. Their performance estimating the objectives are compared in Figure 5.

A fourth model was trained only using the feature identified as "most important" (Average Soil Surface Temperature). Without sizing information, it was incapable of estimating the proportion of heating and cooling loads served, but it achieved R^2 scores of 0.74 and 0.88 for estimating cooling SCOP and heating SCOP respectively.

Outlook and Conclusions

This study has demonstrated that ANN methods can predict GSHP performance and system loading with sufficient accuracy ($R^2 > 0.98$) within a narrow scope of building types and ground conditions, and that the process identifying important features in GSHP performance modeling can be efficiently handled with those same meta-models.
Furthermore, the study provided preliminary results of a comparison of simplified models that better reflect the limited information available in early stages of design, and showed promising results for using computationally efficient ANN meta-models to replace high fidelity simulation, where only preliminary performance and loading proportion estimates are needed. As part of this approach, additional load characterization using Discrete Fourier Series decomposition was also shown to provide significant benefit for reducing prediction error.
The most important feature influencing GSHP performance (by a significant margin) was Average Soil Surface Temperature. This aligns with most simplified models for GSHP performance, which identify correlation coefficients for inlet temperatures (from the field); however, the results from the models trained on reduced feature sets demonstrate that using only the most important features is not sufficient to maintain that prediction accuracy. The potential loading proportion of the GSHP plants was influenced by a more varied set of features.
There were notable limitations to the study that prevent generalize-ability. Instead, this study indicates promising direction of investigation that could be continued in a variety of ways, including:

- Including additional characteristics/features (expanding on Fourier Series load profile decomposition)
- Refining feature selection process (applying a more statistically rigorous DOE)
- Expanding scope of study (parameters, building types, weather files, etc.)
- Bringing in more detailed system modeling for design support (both GSHP plant and GHE field, over longer time horizons)

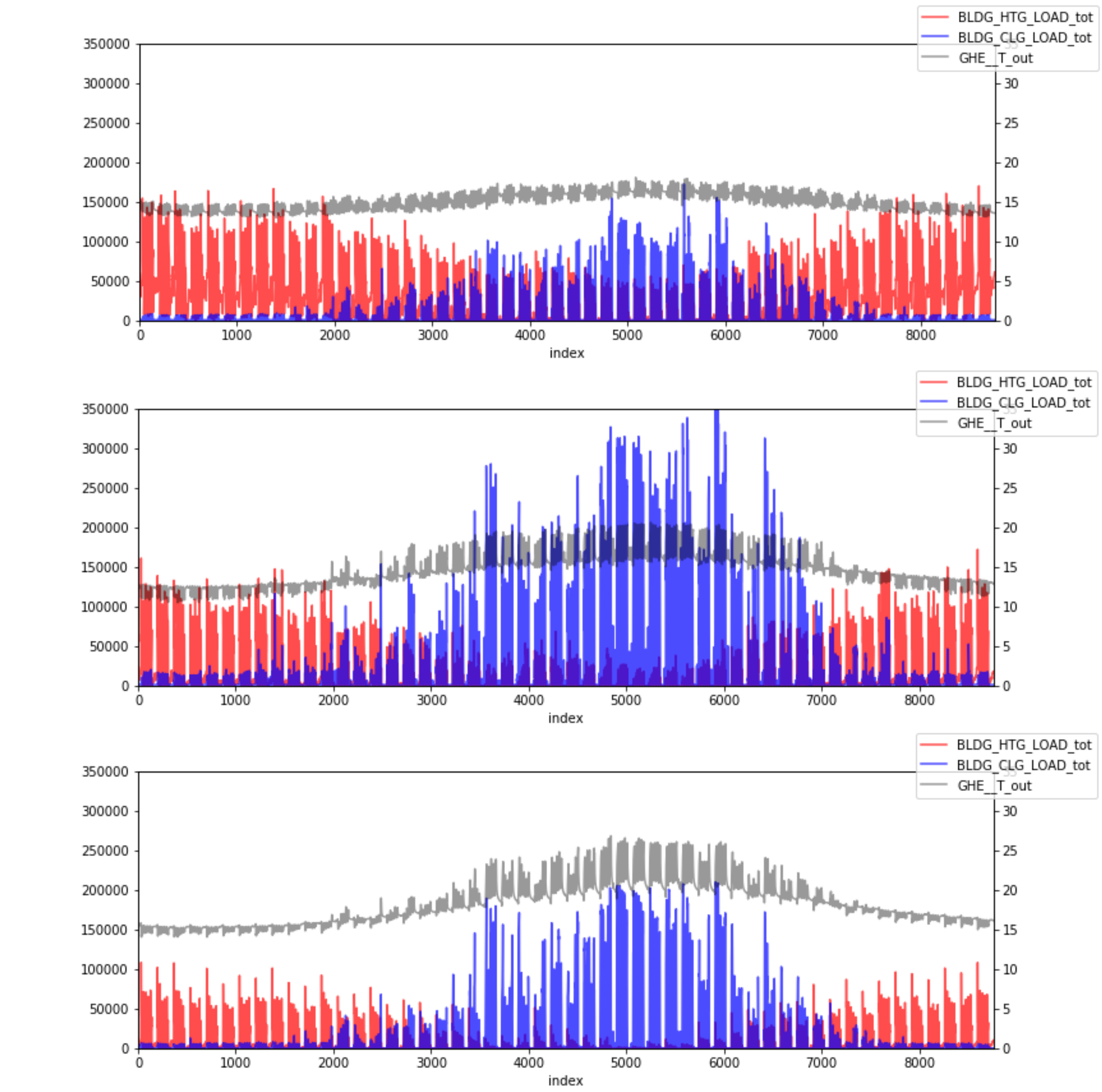

Figure 2: Annual heating and cooling load profiles with temperature of fluid leaving ground, (sample for 90th, 50th, and 10th percentile total heating demand)

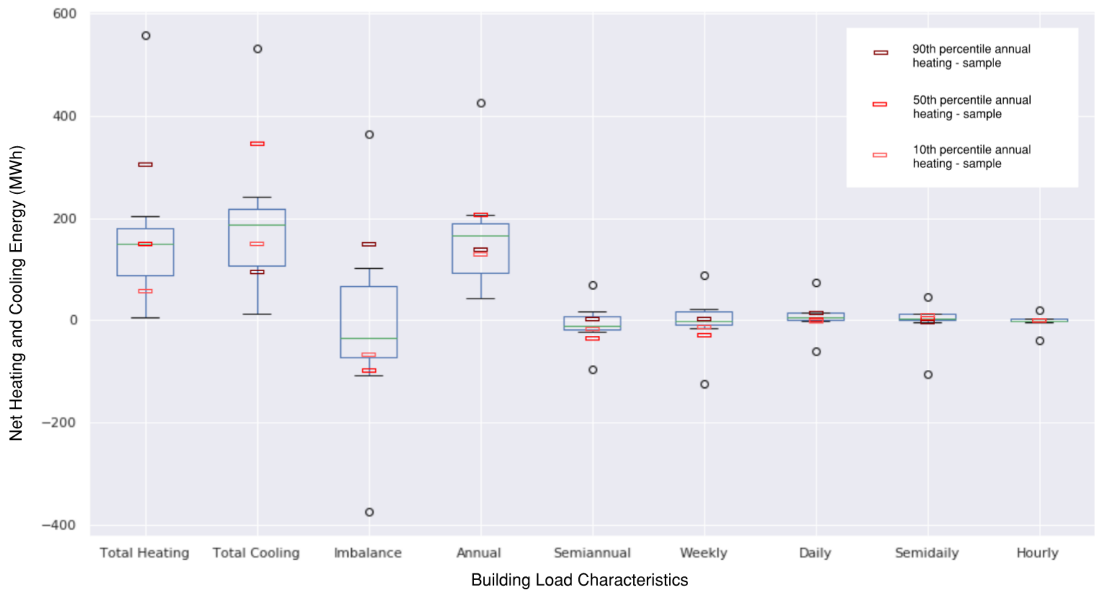

Figure 3: Distribution of characteristic results across full solution set (sample size: 9440)

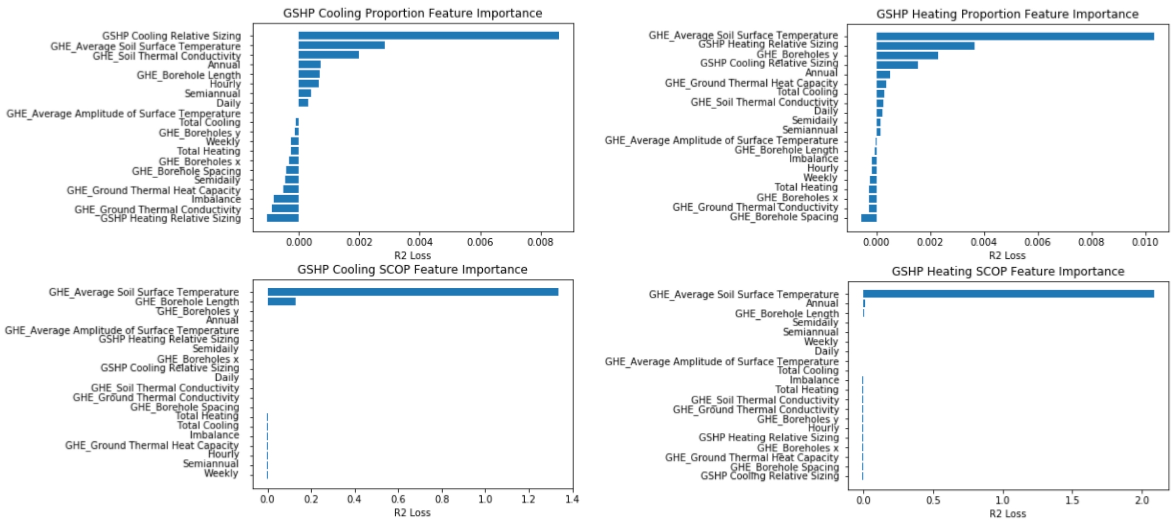

Figure 4: Feature importance based on R2 score loss for objectives across test set

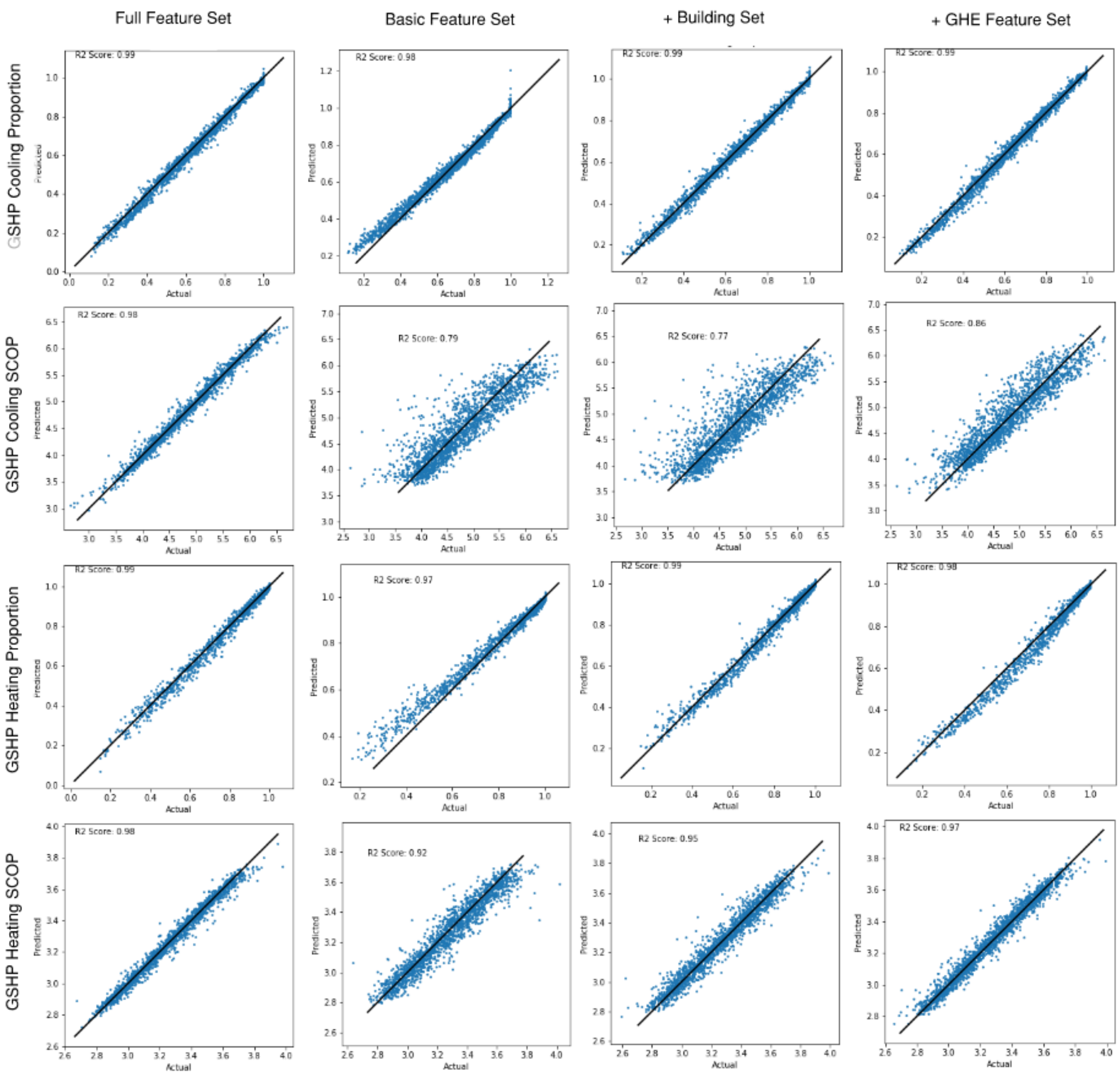

Figure 5: Predicted vs. actual objective performance across test sets

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