Development of Building Specific Metamodels using Washington, DC Benchmarking Data to Infer Interval Data

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**ABSTRACT**

This paper will discuss the development of metamodels that were generated to quickly return realistic annual hourly load profiles of commercial buildings. The metamodels were generated and calibrated to a small set of building characteristics disclosed in the 2018 benchmark data for Washington, DC, USA. Traditionally the effort to use building energy modeling (BEM) to generate detailed 8,760 models that are calibrated to actual data is time-consuming and difficult to achieve. This paper demonstrates how metamodels generated from a large parameter space of BEM simulations (with multiple covariates) can be used to calibrate benchmarking data. The results are a set of fast running metamodels that can return hourly electricity or gas consumption for a subset of buildings in the benchmark dataset.

# INTRODUCTION

For many years, several cities have been mandating the release of annual energy data for medium and large commercial buildings. The data published by the cities are typically high-level information about the buildings such as primary (and secondary) use types, number of stories, gross conditioned area, and location. These data also include annual energy consumption broken out by electric and gas usage per year. This paper focuses on using data from Washington, DC provided by the Department of the Energy and Environment (DOEE) disclosure ordinance [1]. DOEE has various sets of data, a public dataset (previously referenced), and a private dataset that is stored in the Standard Energy Efficient Data (SEED) Platform [2].

Using the disclosed dataset, high-level characteristics were extracted for office buildings to generate surrogate models of the building load profiles. For this paper, only the public data was used; however, more granular private data would enable more accurate calibration of the metamodels as the private data includes characteristics such as the number of hotel rooms, number of computers, and more granular usage data such as monthly electricity consumption. The latter private dataset is planned to be used for follow on analysis.

The advantages of metamodels and using a framework to build metamodels allow researchers to easily generate new load profiles based on variables that deemed important to the selected response variables (in this case electricity consumption). If the metamodel performs similar to a fully defined building energy model, then it is advantageous to leverage the metamodel due to the 1) run time of the metamodel, 2) ability to run a new metamodel based on differing building characteristics (assuming the covariates have been exposed), and 3) advantage of easily aggregating multiple metamodel results together to emulate the load seen by the electric grid.

# BACKGROUND

The overall goal of the research will be to determine which buildings in DC should be targeted for potential upgrades based on various metrics such as site (or source) energy use intensities over time, grid-interactive metrics, demand flexibility, and carbon emissions. However, the first part of this analysis is “simply” the inspection of the disclosed benchmarking data, the use of BEM (specifically OpenStudio [3] and EnergyPlus [4]) to fill out a large parameter space, the regression of the BEM results into metamodels using the Metamodeling Framework [5], calibration of metamodels to reported benchmarking disclosure data, and the demonstration of building load aggregation. The second part of this research will be the use of the developed metamodel for each building to emulate building measure upgrades and determine impacts on various building and grid metrics such as peak demand, time of demand, total building consumption, etc. The outcome will be a ranked list of buildings that should undergo improvements based on the various metrics. The ability to have a ranked list would provide DOEE the ability to design efficiency or demand programs to target various goals.

Many governments and local municipalities in the United States and throughout the world have adopted energy rating standards, benchmarking requirements, mandatory disclosure, and more recently mandatory audits with required upgrades based on simple payback calculations [6]–[9]. Many of these policies are requiring public disclosure of building characteristics and energy consumption. Based on these disclosed data, there are many companies, researchers, and students using the data to better understand the built environment and to provide better policy direction for local governments.

Furthermore, the availability of load profiles of commercial buildings are still limited and is important when conducting capacity planning or evaluating the total impact of buildings on the grid, environment, or available resources. The ability to rapidly create load profiles will help researchers and designers to better approximate the impact of buildings on the built environment and the electric grid.

## Literature Review

There are several distribution network modeling tools including OpenDSS, GridLabD, PSCAD, and PLEXOS. Presently, there does not appear to exist a universal tool that integrates all the components of the grid, from the power plant to the building operations. The grid tools leverage loads from commercial/residential buildings, photovoltaics (PV), electric vehicle (EV) charging profiles, and other loads as simple static files. These low voltage (LV) and medium voltage (MV) data are integrated into the grid tools as time-based profiles from CSVs, GIS data, or other sources [10]. The microgrid and transactive controls tools start to require more integrated connection the building(s) being analyzed, however, the data sets representing commercial buildings are still statically defined. Hong, et al. showed a microgrid still used energy schedules (loads) as defined by OpenDSS [11] for a commercial building microgrid analysis.

Historically, metamodels have been generated for commercial buildings for many different use cases. The term metamodel is used in this research; however, there are many similar terms including response surface models, surrogate models, reduced order models, emulators, and regression models. They have been successfully deployed to determine an approximate asset rating [12]–[14], the use of metamodels for enabling better design of buildings [15]–[17], and an apropos use of metamodels to approximate next day energy consumption and peak demand [18].

Building energy modeling (BEM) has been the cornerstone method for calculating sub-hourly to annual metrics for the residential and commercial building domain. The results of BEM are used in the design, analysis, compliance, and control of buildings. There are, however, drawbacks to using BEM, specifically, BEM requires very detailed and a large number of inputs of the building, can be slow to run full annual simulations, can be difficult to abstract out high-level measures (e.g., changing window to wall ratios), and rarely do the models represent the intricacies of the real world (typically due to idealized schedules and performance characteristics [e.g., infiltration, ventilation, etc]). OpenStudio [3] and the OpenStudio Analysis Framework [19] are abstraction layers on top of EnergyPlus [4] allowing for easier model generation using prototype buildings [20] and OpenStudio measures [21]. OpenStudio Analysis Framework enables algorithmic workflows such as optimization, calibration, and parameter space generation using methods such as Sobol or Latin hypercube sampling (LHS).

The Metamodeling Framework [5] was initially developed to create simplified building models connected to a district heating and cooling system through an energy transfer station where the covariates exposed a few select variables to quickly approximate the total energy consumption at any time, t. The Metamodeling Framework currently has three different metamodels: multivariate ordinary least squares, support vector machines, and random forests. Von Rhein [22] demonstrated the integration of the metamodels in CSV format into Modelica to optimize the district layout of a near-ambient loop district energy system.

The use of metamodels for calibration has been used in Autotune [23]. This project leveraged the generation of millions of EnergyPlus simulations of a large parameter space and various machine learning algorithms including linear models, support vector machines, and various types of neural networks. It is important to note that the majority of the calibration methods use data at a higher frequency than annual data, typically monthly or hourly data. This project only had public access to annual data, therefore, it is inherently understood that the search is even more under-determined than conventional methods using sub-annual data. Nonetheless, the advantage of calibrating actual data to a metamodel is the ability to more fully search the parameter space as metamodels run much quicker than building energy models.

# METHODOLOGY

This paper described the generation and calibration of metamodels to actual buildings in the Washington DC area. In general, the steps needed to conduct this research involved the following:

1. Investigate the publicly disclosed benchmarking data.
2. Use the building type and building characteristics to inform the BEM parameter space that needs to be modeled.
3. Use (and extend) OpenStudio, OpenStudio Measures, and OpenStudio Analysis Framework to model a large parameter space of buildings using LHS.
4. Use (and extend) the Metamodeling Framework to create random forest metamodels of the parameter space
5. Select a few exemplar buildings from the DC dataset to calibrate the annual data to the metamodel. Use the non-sorting genetic algorithm II (NSGAII) algorithm as developed in the Platypus package[[1]](#footnote-1).
6. Plot the Pareto front of each building and determine the “best building” based on the results of the multi-objective optimization.

Each of the steps above will be discussed in more detail in the following subsections.

## Disclosure Data

The first step of the methodology is to determine what data are available in the Washington, DC disclosure data. Note that this section is a mix of methodology and results as the remaining methodology sections require an understanding of the type of data available in the benchmarking disclosure. Based on the data publicly available, data have been reported from 2010 through 2018. There were 54 property types ranging from worship facilities, urgent care, strip malls, to offices. In 2018, there was a total 1,798 disclosed data; however, many building types only had a few buildings being reported. Figure 1 shows the breakdown of building types for 2016, 2017, and 2018 reporting periods where more than 15 buildings are reported.

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Figure 1. Histogram of building types for Washington, DC

As shown, multifamily housing and offices are the most common building being reported. To prove the workflow on a few select buildings, histograms were generated for each of the property types for a subset of interesting variables which included reporting period, floor area, year built, site energy use intensity (EUI), total electricity consumption, and total gas consumption. Based on the histograms the probability distribution function (PDF) did not change significantly over the reporting years, see Figure 2.

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Figure 2. PDF of year built for office buildings in 2016, 2017, and 2018

It was determined that choosing the medium office building during 2018 was a reasonable starting point for the analysis. Further constraints were applied to randomly select a subset of office buildings and included: year built between 1980 and 2010, site EUI between 30 and 90 kBtu/ft2/year, and the floor area between 20,000 and 75,000 square feet. There were 13 buildings that met the constraints with a median year built of 1986 and a median floor area of 54,729 square feet (mean of 55,447 square feet). Of the 13 buildings down selected, 3 were randomly chosen for detailed analysis.

Table . Actual building parameters

|  |  |  |  |
| --- | --- | --- | --- |
| **Input** | **B0** | **B1** | **B2** |
| Address | 1146 19th Street | 3307 - 3311 M ST NW | 1235 W Street NE |
| Floor Area (ft2) | 47083 | 54560 | 38964 |
| Year Built | 1986 | 1991 | 1993 |
| Site EUI (kBtu/ft2/year) | 59 | 84.1 | 43.9 |
| Electricity Use (kWh) | 814,091 | 1,344,206 | 323,703 |
| Natural Gas Use (Therms) | 0 | 0 | 6042.4 |

## Building Energy Modeling

Metamodels are good an interpolation and poor at extrapolation, so the building energy models must represent the parameter space required for the calibration. Therefore, the characteristics discovered in the DC disclosure data in 3.1 were used to create the parameter space the building energy models. This analysis leveraged mostly already developed OpenStudio measures to generate prototypical building models based on high-level parameters; however, a new reporting measure was developed to extract the time series data into a CSV which will be used later for training the metamodels. The results of interest are the hourly electricity and gas consumption of the entire facility. The OpenStudio Parametric Analysis Tool [24] was used to set up an algorithmic workflow where an OpenStudio measure’s argument is converted into a variable with either a discrete or continuous distribution.

Table 2. List of BEM measures and variables

|  |  |  |  |
| --- | --- | --- | --- |
| **Measure Name** | **Variable Name** | **Type** | **Value** |
| Building from Building Type Ratios | Primary Building Type | Static | MediumOffice |
| Floor Area | Continuous (Uniform) | [20,000, 75,000] ft2 |
| Number of Stories | Discrete (Uniform) | [2, 3, 4, 5, 6] |
| Building Rotation | Continuous (Uniform) | [0, 180] ° |
| Aspect Ratio | Continuous (Uniform) | [1, 4] |
| Window to Wall Ratio | Continuous (Uniform) | [0.2, 0.8] |
| Change Building Location | Weather File Name | Static | USA\_VA\_Arlington-Ronald.Reagan.Washington.Natl.AP.724050\_TMY3.epw |
| Typical DOE Building | Target Standard | Discrete (Uniform) | [Pre-1980, 1980-2004, 90.1-2004, 90.1-2008, 90.1-2010] |
| Heating Source | Discrete (Uniform) | [Electricity, NaturalGas] |
| Hours of Operation Start Time | Continuous (Uniform) | [6,10] |
| Hours of Operation Duration | Continuous  (Uniform) | [6,16] |
| Internal Loads | LPD Multiplier | Continuous  (Uniform) | [0.5, 10] |
| People Multiplier | Continuous  (Uniform) | [0.5, 10] |

A Latin hypercube sampling algorithm with 300 samples was used to generate individual building energy models of the entire parameter space. Upon completion of the simulations, custom Python processing scripts are used to add in the features of the building to each timestep of the gas and electricity consumption as well as combine all the time series results into a single large file. These combined files can become quite large ranging in gigabytes of uncompressed data.

Table 2 shows the list of measures and variables selected for the DC benchmarking data.

## Metamodeling

The results of the building energy models were regressed to generate metamodels using random forests. A random forest is a collection (or forest) of decision trees. The random forest can perform as a regressor or as a classifier. When running as a regressor, the returned value is an average of the result of each decision tree evaluated at the inputs (covariates).

The metamodeling leveraged a previously developed work termed the Metamodeling Framework [5]; however, several extensions were needed to handle the proposed use case which includes:

* Addition of categorical variables encoding using one-hot encoding
* Removal of energy transfer station-specific data processing
* Rewrite BEM post-processing helper scripts with Python (previously Ruby)
* Address a few bugs including calculation of the day of the week.

Building energy modeling can require hundreds to tens of thousands of inputs which leads to the advantage of metamodeling to reduce the number of inputs to only a handful. Determining which building energy modeling input is important is difficult and in this research was selected based on prior research and building energy modeling expertise. Table 3 lists the covariates selected for the medium office building energy models. Note that many of the covariates are similar to the arguments of the measures in the building energy model. The major difference between a measure argument and the covariates is that a measure argument is an aspirational value whereas a covariate is a reported value of the simulation. For example, a measure can request a window to wall ratio of 0.9, but due to constraints in geometry, doors, and sill heights, the actual model may only obtain a window to wall ratio of 0.8. The latter value (0.8) is the covariate value used in the metamodeling framework.

Table 3. List of metamodel covariates

|  |  |  |
| --- | --- | --- |
| **Variable** | **Data Type** | **Example Value** |
| Month | Integer | 1, 2, 3, … |
| Hour | Integer | 0, 1, 2, ... |
| Day of Week | Categorical | 0=Sunday, 1=Monday |
| Outdoor Drybulb Temp | Float | 25°C |
| Outdoor RH | Float | 75% |
| Building Type | Categorical | Medium Office |
| Floor Area | Float | 25,000 ft2 |
| Floor Height | Float | 10 ft |
| Number of Stories | Integer | 1, 2, 3, … |
| Building Rotation | Float | 45° |
| Aspect Ratio | Float | 0.5, 2.0 |
| Window to Wall Ratio | Float | 0.40 |
| Target Standard | Categorial | 90.1-2004, 90.1-2007 |
| Heating Source | Categorial | Electricity, Natural Gas |
| Hours Start Time | Float | 6.25, 7, 8 |
| Hours Duration | Float | 12, 14.5 hours |
| Lighting Power Density | Float | 1 W/ft2 |
| Average People Density | Float | 100 People / 100 ft2 |

The input data from the building energy models are first downsampled to prevent overfitting the metamodels. The downsampling is a random selection of the hourly data, and in this case, was set to 5% of the near 2.6 million samples. The resulting downsampled dataset is split into a training set, test set, and validation set. The training set was set at 70%.

K-fold cross-validation (k=3) was performed on the random forest regressors with a grid search using the following parameters:

* Max depth – auto, 3, 6
* Max features – 0.5, 0.75
* Minimum samples per leaf – 1, 2
* Minimum samples per split – 3, 5
* Number of trees – 50, 100

The metric of interest is the Pearson Correlation, normalized mean bias error (NBME), and the coefficient of variation of the root mean square error (CVRMSE).

The Metamodeling Framework enables the user to persist the metamodel to be loaded and used later for subsequent analysis. The framework has an Analysis Definition specification allowing for a JSON file to be loaded and evaluated using either specific covariates, ranges of covariates, or a mix of both. In addition, an EnergyPlus weather file (EPW) can be loaded and evaluated in the Metamodeling Framework. For this analysis, a typical meteorological year (TMY) file was used to run both the calibrations. These analysis definition files are persisted which are later loaded for use in the calibration step.

## Calibration

Calibration is used to tune the inputs of the metamodel analysis definition files. Calibration at its core is optimization. The problem here is defined in (1). As defined, the problem is significantly under-determined due to the number of variable combinations that can result in a viable solution. Also, the problem is a mixed-integer problem as there are integer, floats, and categorical variables. The

|  |  |
| --- | --- |
| where = actual annual electric energy  = modeled annual electric energy  = actual annual gas energy  = modeled annual gas energy  = building parameters (e.g., LPD, Number of Stories)  = error between modeled/actual electric/gas energy  s.t. constraints shown in Table 4. | (1) |

Based on the setup of the optimization, it was determined to use a non-sorting genetic algorithm (version 2) to run the calibration as the problem is multi-objective. The objective functions are the annual gas consumption and annual electric consumption. The variables are shown in Table 4.

Table 4. Optimization variables

|  |  |  |
| --- | --- | --- |
| **Variable** | **Data Type** | **Range** |
| Lighting Power Density | Real | [1, 20] |
| Number of Stories | Integer | [1, 13] |
| Aspect Ratio | Real | [1, 5] |
| Hours Start | Real | [6, 10] |
| Hours Duration | Float | [8, 16] |
| Heating Source | Categorical | [Electricity, NaturalGas] |

The analysis definitions described briefly in 3.3 are the starting point of the calibration. The analysis definitions are defined in a JSON file and the optimization variables were marked as replaceable. The evaluation function, written in Python, replaces the variable values from the optimization algorithm in the analysis definition file. The values are replaced using Python’s Jinja2 template framework[[2]](#footnote-2).

The optimization algorithm was the NSGAII algorithm with the following parameters: 6 variables, 2 objective functions, 15 population size, 30 max iterations, tournament selector initial conditions. Each calibration simulation input file was stored in its directory along with the results.

# RESULTS AND DISCUSSION

This section discusses the results of the building energy modeling, the performance of the metamodels, and the calibration.

## Building Energy Modeling

In total, 300 building energy models were run. Each model took ~240 seconds depending on the modeling parameters. The models were verified by randomly selecting a simulation and inspecting the OpenStudio results. Figure 3 shows the results of all the simulations; the blue lines represent individual simulations and the vertical parallel lines each represent input and output variables.

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Figure . A parallel coordinate plot of simulations   
(not meant to be legible)

The unmet hours over all the simulations on average was 225 hours. This was deemed reasonable for a large number of autogenerated simulations.

## Metamodeling

One of the advantages of random forest metamodels is the ability to extract variable importances. Figure 4 and Figure 5 graphically show the importance of the electricity and gas response variables. As shown, for electricity (the response of most interest) the most important building characteristic variables are the floor area, lighting power density, and the hours of operation start/duration.

The random forest models took ~262 seconds to build including the time needed for cross-validation. The building of the random forest was accomplished using parallel processing. The PCC was 0.991 and 0.784 for the electricity and gas model respectively. The poorer PCC for the gas metamodel is most likely attributed to the lack of the number of simulations since heating source could be either electricity or natural gas, or the potential lack in covariates that pertain to gas consumption.

The results of the leave one annual simulation out validation dataset showed that the NMBE was 24.8 and 3.79 for the electricity and gas model respectively. The CVRMSE was 38.8 and 34.9 for the electricity and gas model respectively. These values are slightly larger than the accepted 15 and 5 for CVRMSE and NMBE, respectively, as defined by ASHRAE Guideline 14. The persisted metamodels were around 80MB and required 0.085 seconds to load into memory. Each run of the metamodel for an entire 8,760 simulation took 0.037 seconds. This load time and run time demonstrates the clear advantage of leveraging metamodels when time-consuming tasks exist such as calibration and optimization.

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Figure . The relative importance of electricity use response

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Figure . The relative importance of gas use response

## Calibration

The calibration of the models took ~780 seconds for each building; however, the calibration was accomplished using a single core. The calibration method can be parallelized as the simulate function is slow (hundredths of seconds) compared to the processing time of evaluating the objective function. The implementation of parallelization was not investigated in this research. The average number of metamodel simulations required until stopping criteria were met was ~250 simulations.

Figure 6 shows the graphical results of the calibration where the X-axis shows the error of the electricity metric, and the Y-axis is the error in the gas metric.

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Figure . Results of building zero calibration

The analysis required manually selecting the best building and was chosen as the point closest to the 0,0 origin. In the image above, the error is quite low, however, the other two buildings had a much higher error. There is more than one solution as a Pareto front is generated due to the multi-objective nature of the problem. Also, note that the error of the gas calibration did not reach zero. The reason for an always non-zero gas error was likely due to an inaccurate selection of the building heating system. Even though the heating source has high importance for the gas response, it appears that since the random forest averages the results of the decision trees, that the value is non-zero most of the time. A recommended solution would be to generate a metamodel of metamodels allowing for the heating source variable to become the “most important” variable since the existence would result in a binary variable of exists or does not exist, and a value of zero or non-zero.

Figure 7 shows the electricity heat maps for each of the selected 3 buildings. As demonstrated, the biggest change in the electricity profiles is the stretching of the hours of operation and the peaks during the summer months.

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Figure . Electricity heat maps for the 3 calibrated buildings in order B0, B1, B2

The calibrated building characteristics are shown in Table 5. Note that this is only a subselect of all the input variables needed to run the metamodel as several of the values were fixed based on the lack of relative importance in the previous section.

Table . Results of building calibrations

|  |  |  |  |
| --- | --- | --- | --- |
| **Input** | **B0** | **B1** | **B2** |
| Floor Area (ft2) | 47083 | 54560 | 38964 |
| Number of Stories | 4 | 6 | 11 |
| Aspect Ratio | 1.4 | 4.9 | 3.5 |
| Hours Start | 6 | 9:45 | 9:30 |
| Hours Duration | 9 | 14 | 8:45 |
| Lighting Power Density (W/ft2) | 16 | 19 | 1.4 |
| Heating Source | Electricity | Electricity | NaturalGas |

# CONCLUSIONS

The ultimate goal of the metamodeling and calibration effort was to generate a set of metamodels that can be used to calculate an annual electric (and gas) load profile. The ability to load in a metamodel with select covariates can significantly reduce the time needed to build a fully defined physics-based building energy model. In addition, the ability to load multiple representations of actual buildings (e.g., from a benchmarking disclosure dataset) can be used to generate grid-level load profiles. Figure 8 shows the aggregated electric load by using the calibrated metamodels to determine the peak week for the system of three buildings.

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Figure . Aggregating multiple electricity loads

The hourly (or more granular) data generation can be easily exported to a CSV file (or .mat file for Modelica) which can then be used for OpenDSS or other grid dispatch planning software.

Based on the calibrated results, the buildings’ heating sources were correctly identified if assuming that a building without natural gas reported most like has electric heating. In reality, the building probably has district heating; however, for the data given the prediction seems reasonable.

# FUTURE WORK

This analysis merely demonstrated the functionality of generating metamodels that can be used to quickly generate load profiles; however, there exist many other future work opportunities including:

* Run a sensitivity analysis on the building energy models to better select important variables,
* Validate metamodels against the real buildings,
* Use more granular data from SEED which contains the monthly electricity and gas consumption instead of the annualized metric,
* Use actual meteorological weather data instead of typical meteorological weather and utilize the year over year benchmark disclosure data,
* Replace the Platypus package for running the NSGAII algorithm with a more versatile package,
* Investigate the use of different optimization algorithms such as particle swarm optimization (PSO).

All of the source code used to generate the analysis above is available on GitHub under https://github.com/nllong/dc-metamodeling.

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1. <https://pypi.org/project/Platypus-Opt/> [↑](#footnote-ref-1)
2. <https://pypi.org/project/Jinja2/> [↑](#footnote-ref-2)