

# Streamlining building energy efficiency assessment through integration of uncertainty analysis and full scale energy simulations

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## ABSTRACT

Asset Score is a standardized rating system and tool for assessing a building's energy-related systems in the United States. The web-based tool models building energy use under standard operating conditions to rate the energy efficiency of the as-built building systems and enable level comparisons of building assets. With basic characteristics entered by users, the tool creates simplified EnergyPlus building models to support the rating analysis. However, even with a reduced set of model inputs, data collection remains a challenge and the commercial building market demands a more simplified entry point to the rating system. This paper discusses a hybrid method that combines regression models with real-time simulations to allow users to enter as few as seven building parameters to quickly assess the building energy performance prior to a full-scale analysis. Built upon large-scale building stock simulations, a random forest approach was used to develop a set of regression models for various building use types. The majority of the Asset Score tool inputs were sampled extensively and fed into the regression models. These were combined with inferred inputs and user-defined uncertainty levels to create a distribution of possible energy use intensities for the building and its Preview score. With additional user inputs, the regression model can be transferred to an energy model for a full-scale energy simulation. The streamlined Asset Score Preview assessment provides an easy entry point to a full Asset Score assessment. It also enables users who manage a large number of buildings to screen and prioritize buildings that can benefit most from a more detailed evaluation and possible energy efficiency upgrades without intensive data collection.

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## 1. Introduction

Asset Score, developed by the Pacific Northwest National Laboratory (PNNL) for the United States Department of Energy (DOE), is a national web-based rating system to help commercial and multi-family building owners, operators and tenants understand the current and potential performance of a building's assets, which include building envelope (roof, walls and windows), mechanical systems and electrical systems. The Asset Score is calculated based on standardized building operation conditions independent of an individual building's operational decisions. The Asset Score is a simple 10-point scale where the higher the score, the more efficient the building asset is relative to its population of peers. The population is constructed via robust building stock simulations for each building use type [1]. The web tool is built on a centralized Energy-

Plus and OpenStudio modeling engine to reduce the implementation cost for the users and increase standardization compared with an approach that requires users to build their own energy models [1]. Users can enter between 20 and 100 building characteristics to obtain a standard Asset Score Report, which includes scores, energy use breakdown, efficiency rankings of building components and opportunities for energy efficiency improvements.

The feedback from pilot evaluations conducted in 2012 and 2013 suggested that data collection remains a challenge for widespread adoption of this rating system, even with a reduced set of model inputs [2]. To address this barrier, Asset Score Preview (hereinafter Preview) was developed to allow users to start assessing energy efficiency of a building with as few as seven inputs. The seven building characteristics form the basis for inferring the remaining parameters to complete a full energy model. Preview requires high-level inputs, including building name, location, vintage, conditioned floor area, number of floors, predominant use type and orientation. A few additional inputs regarding years of retrofit for

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lighting, heating, ventilation and air conditioning (HVAC), and service hot water systems can be provided if available. On the basis of these limited inputs, Preview's defaults database is able to populate the remaining data points required for creating a complete Asset Score model, which is then analyzed for energy efficiency and energy savings. Using a regression model, Asset Score then calculates the possible range of the building's energy use based on stock simulations and uncertainty analysis. The estimated energy use range is mapped to the Asset Score scale to provide users with an estimated score range. Users can choose to convert their building from the Preview mode into a full Asset Score assessment mode by entering additional building characteristics. This paper will discuss the methodology of using stock simulation, uncertainty analysis and random forest sampling to develop the Preview analysis and the streamlined process of integrating regression analysis and full-scale energy simulation.

## 2. Asset score preview simulation framework

### 2.1. Overview

The Asset Score Tool is modular in design for clean separation of functionalities and flexible software development and testing. The backend simulation process of the Asset Score Tool was integrated within a framework to perform a sensitivity based on energy use intensity (EUI) distributions. The EUI distributions are the basis for the 10-point scale for each use type [1,3]. The analysis framework was also used to develop the regression methodology used to calculate scores for Preview buildings. Details on the regression methodology used and parameter space evaluation are discussed in the following sections.

### 2.2. Asset score tool architecture

The core components of the Asset Score Tool Application [4] are divided into the following five subsystems, as shown in Fig. 1.

1. User Interface: The user interface is the outward-facing portion of the tool that allows users to define the building characteristics. The user interface offers two input modes: (i) Asset Score Full and (ii) Asset Score Preview. In the full input mode, a user can draw the building geometry and define building specific parameters such as construction types, mechanical system types and efficiencies, electrical system details and more. The Preview input mode limits user inputs to seven data points, providing defaults for the remaining inputs and a capability for the user to view and edit the default values. The defaults database is discussed further in the next section.
2. Asset score application: The Asset Score Application forms the core of the Asset Score Tool. It translates all user inputs into the Asset Score schema, which is then sent to the Analytical Engine. It also validates the data model and acts as the intermediary between the Analytical Engine, Simulation Framework and Report Generator. For buildings submitted through the Preview input mode, the Asset Score Application adds missing building attributes through the defaults database, providing a complete Asset Score data model to the Analytical Engine.
3. Analytical Engine: The inference capabilities of the Facility Energy Decision System, or FEDS [5], is used to fill any missing data that needs to be inferred (e.g. wall/roof U-factors as a function of building vintage). Additionally, FEDS is used to evaluate energy efficiency improvement options, as noted below. All inferred data points and user inputs are sent to the simulation framework through the standard data format of Asset Score XML (AS XML).
4. Simulation Framework: The simulation framework is a combination of EnergyPlus and OpenStudio. OpenStudio articulates

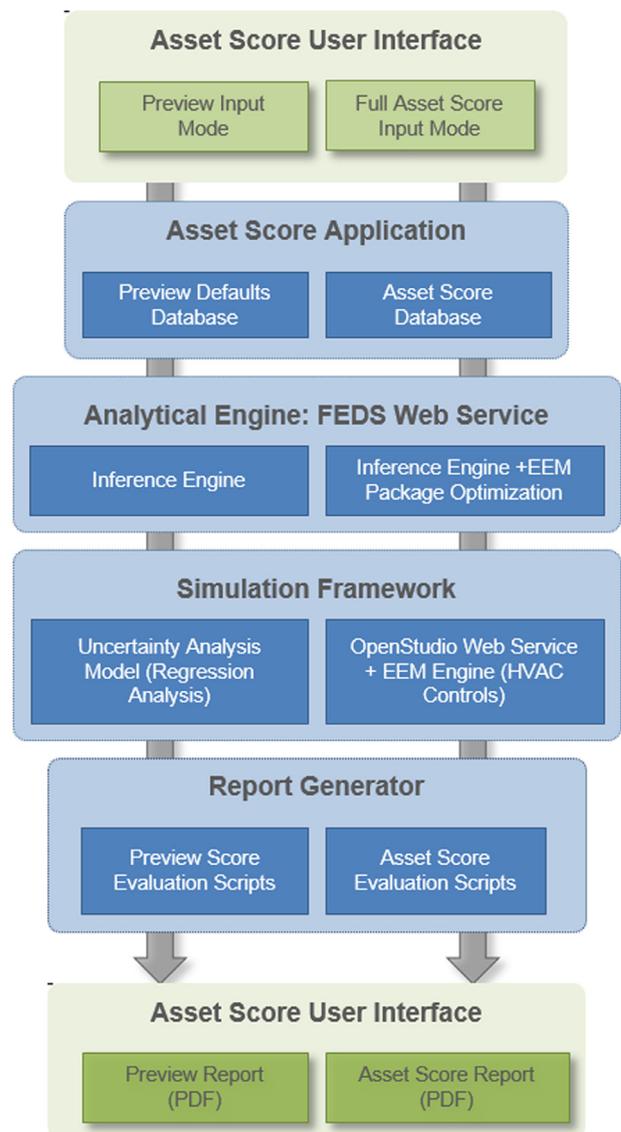


Fig. 1. Asset score tool architecture.

energy model and EnergyPlus runs simulations. The framework is used for buildings submitted through the full input mode. Buildings submitted through the Preview input mode go through the uncertainty analysis framework, which allows for a quick assessment of building components based on a regression model. The uncertainty analysis framework is explained in detail in Section 3.

5. Report Generator: The Report Generator runs a series of post-processing scripts to calculate building scores and generates the Asset Score Report. Buildings going through the full model receive a report with a current score and a potential score (after recommended retrofit) based on the whole building energy simulation runs. Preview buildings receive a report with a score range of three or four points based on the uncertainty analysis through the regression engine.

### 2.3. Process

The defaults database is built upon the DOE reference buildings [6], the prototype buildings [14] and the Commercial Buildings Energy Consumption Survey (CBECS) [27]. Based on a building's location, year of construction, use-type and conditioned floor area,

the Asset Score Application identifies the remaining data points, including the construction types for all envelope components, basic geometry configuration such as aspect ratio and window-to-wall ratio, typical HVAC system type and service hot water system type. The year of construction is used by the defaults database and the FEDS Analytical Engine to infer the typical technologies and their efficiencies based on the building vintage. FEDS was developed by PNNL to facilitate quick and scalable building energy audits and analyses over single- and large groups of buildings [5]. The FEDS inferences are derived from multiple sources and techniques, including dummy variable ordinary least squares regression of CBECS data based on age, use type, size, and climate, equipment efficiency standards, building energy codes and adoption rates, and ASHRAE (The American Society of Heating, Refrigerating and Air-Conditioning Engineers) handbooks, among others. These defaults are made visible to the user, who can verify the value, edit the value or mark a default value as unknown. Each user indication results in the default value being marked as “certain” or “uncertain” within the Asset Score Application. A verified or edited value is translated to the uncertainty analysis model as a certain input, and a default value marked as unknown by the user is translated as an uncertain input. The inputs that are not displayed for user verification are evaluated as uncertain for all applicable scenarios. These include system controls (such as fan control, energy recovery ventilation, demand control ventilation, daylighting control and occupancy sensor control, among others) as well as building geometry inputs (such as floor-to-floor height, building dimensions and aspect ratio). This allows Preview to run a quick analysis, with the more detailed model inputs provided through the full input mode. The complete Asset Score data model is sent to the uncertainty analysis model to determine its EUI range.

The uncertainty analysis model estimates the EUI range (within 95 percentile of sampled results) as well as the mean EUI for the building with all the input values and associated uncertainties. The EUI range is post processed to give the corresponding score range. An Asset Score Preview report provides the current score range, potential score range and estimated potential energy savings. The estimated savings are based on similarly scored buildings that have been analyzed in the full Asset Score Tool. The following sections explain the development of the regression models and the uncertainty analysis process for Preview.

### 3. Development of regression models

The data challenge presented for this analysis is how to construct an underlying dataset that covers a variety of occupant- and mission-normalized commercial building use types and building characteristics across a wide range of vintages and geographic locations. Building stock modeling is a proven technique; however, the permutations associated with general stock modeling are more manageable when targeting specific building types, geographic locations or technologies such as investigating potential for achieving net zero-energy buildings [7].

Regression analysis is a popular technique for predicting building energy use. Several regression model frameworks have been explored in depth, with promising results, utilizing linear and non-linear techniques [8]. Novel non-linear techniques for building energy optimization and prediction, as are used in this study, have been explored by a variety of authors, with generally excellent results of percent error under 5%, [10,11], although not as widely adopted as more classic regression models, i.e., linear least squares. For example, the ENERGY STAR Portfolio Manager® [12], a U.S. benchmark for rating commercial buildings based on their utility bills, utilizes a classic weighted ordinary least squares regression to evaluate a building’s source EUI based on user inputs and

**Table 1**  
The building types analyzed by asset score preview.

Building Use Type	Building Use Type	Building Use Type
Assisted Living	Medium Office	Religious Building
City Hall	Multifamily High-rise, Mid-Rise	Retail
Community Center	Multifamily Low-rise	School
Courthouse	Parking Garage	Senior Center
Large Hotel	Police Station	Small Hotel
Large Office	Post Office	Small Office
Library	Post Office	Warehouse (Non-Refrigerated)

the CBECS [13]. Based on the data harvested from the sampling efforts described above, non-linear models were found to provide excellent accuracy when mapping between user-defined uncertainty ranges regarding building characteristics and asset-based EUI. These efforts are discussed at greater length below.

The overall workflow for the development of the regression model and its application using the Asset Score Tool is depicted in Fig. 2. The first step for this analysis is the development of the seed models, which are then used by the OpenStudio Analysis Framework for generating regression models for each building use type. The Asset Score Tool collects the Preview inputs from the user and uses the applicable regression model for computing the building’s score range. As a last step, a PDF report is generated with the Preview score range and made available to the user. Each of these components is explained in greater detail in the subsequent sections.

#### 3.1. Constructing seed models

The important first step for Asset Score is the construction of a representative purpose-fit building energy use database. This database has been developed using Asset Score seed models. Seed models are the initial models from which all subsequent model perturbations stem. Seed models are generated using the PNNL prototype building models [14]. The prototype building models represent 80% of the commercial building floor area in the United States for new construction, including both commercial buildings and mid- to high-rise residential buildings. These prototypes were originally developed for DOE to assess the relative improvement of sequential versions of ASHRAE Standard 90.1. Seed models are simplified prototype buildings generated from the Asset Score Tool; therefore, the levels of detail in these seed models represent buildings to be evaluated by Asset Score. Seed models were created for 22 archetype buildings (Table 1) and closely align with the DOE prototype buildings following ASHRAE Standard 90.1–2004, which was chosen to represent average buildings in the technical development of the Asset Score [1]. The building types were selected based on the building area types defined by ASHRAE Standard 90.1 [15] and were further categorized as small, medium, large or low-rise/high-rise based on the prototype building descriptions. The prototype buildings follow these descriptions as these categorizations define the most typical HVAC systems or other building characteristics (e.g., window-to-wall ratio). For example, a small office is typically served by roof-top single-zone systems, while a large office building is likely to be served by variable air volume (VAV) with reheat systems [16]. These “typical” building characteristics inform the regression analysis for Preview. The seed models are more homogeneous than the prototype buildings. They have rectangular footprints and the internal loads are evenly distributed. All operational assumptions are derived from ASHRAE Standard 90.1–2013, Appendix C [15] and include thermostat setpoints, occupancy and lighting schedule, occupant densities, receptacle loads and schedule, process loads and schedule, ventilation rates.

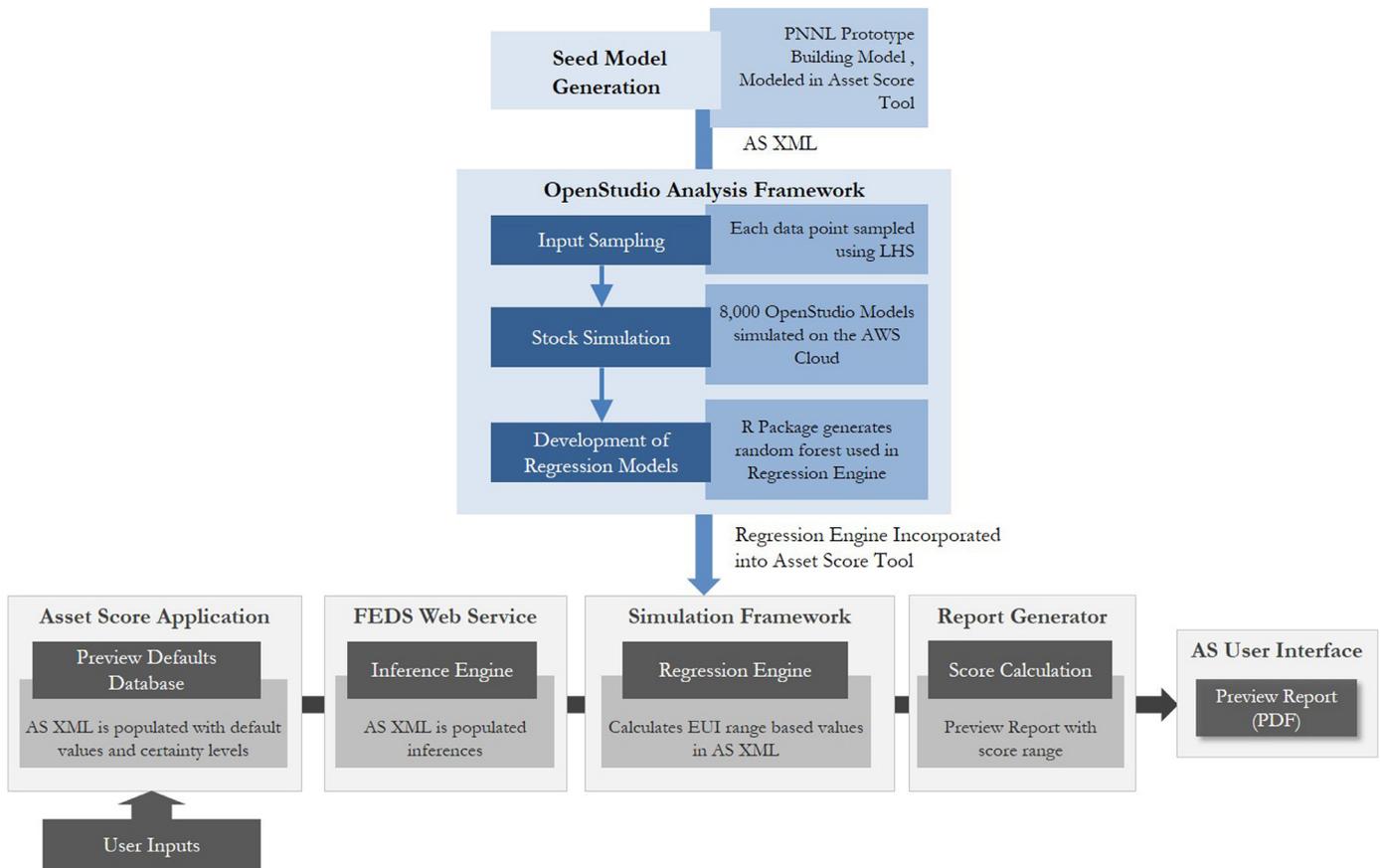


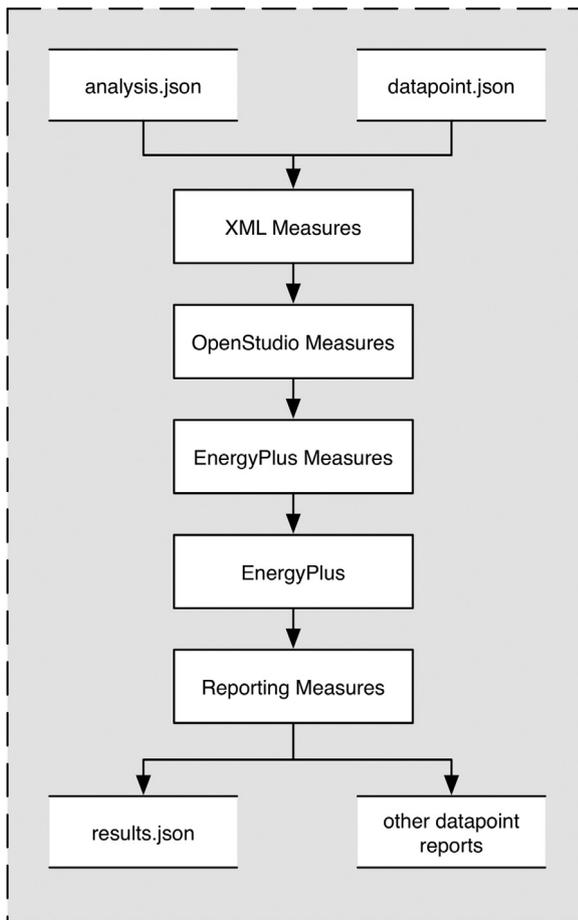
Fig. 2. Overall workflow of the regression analysis process and asset score tool.

Each seed model contains up to 38 input variables (listed in Appendix A), which were identified as important building characteristics from a series of sensitivity analyses [1]. The sensitivity analysis identified all inputs that are important to determining a building's as-built efficiency level, as well as their level of impact on energy use by building use type, size and location. Overall, interior lighting power density, heating system efficiency, floor-to-floor height and air handler fan efficiency are the most sensitive parameters for most of the use types. The ranking of the sensitive variables for different use types changes by climate zone. The variables include climate zone, envelope thermal properties (e.g., U-value), HVAC characteristics (e.g., heating/cooling system efficiency, fan efficiency, system controls), and lighting characteristics (e.g., interior lighting power density, lighting controls). Not included in this list of 38 variables are the standard operation parameters such as schedules, temperature setpoints, plug loads or ventilation rates as well as the HVAC system type, which is not sampled through the regression analysis. Sampling across various system types (including the heating source, cooling source, reheat type, fan control and pump controls, among others) was proven to time- and resource-consuming; instead, multiple seed models were created to represent the most common types of HVAC systems in each building use type. For instance, two seed models were created for medium office to analyze packaged VAV with electric reheat system and packaged single-zone air-conditioning system. At the time of the deployment of the Asset Score Preview, there were 46 models serving as a baseline for all simulations used in the framework. All buildings are modeled as rectangular core and perimeter zone models with the aspect ratio, floor plan area and number of stories as variables.

### 3.2. OpenStudio analysis framework

The seed models were analyzed using the OpenStudio Analysis Framework. The OpenStudio Analysis Framework enables an efficient setup of analyses (e.g., sampling, optimization) by using an Excel-based spreadsheet to select the seed model, algorithm details, variables and outputs. It uses a combination of Ruby, R, OpenStudio and MongoDB to create a cluster of machines in Amazon's Elastic Compute Cloud (EC2) to run the simulations in parallel. The result of the analysis is a .CSV that can be loaded as an R data frame for statistical modeling, with each row representing a single simulation. The columns of data are defined as outputs during the initial setup. The OpenStudio Analysis Framework can run several algorithms, including sampling (i.e., Latin hypercube sampling), batch runs, optimization or calibration. Typically, the OpenStudio Analysis Framework requires OpenStudio models (OSM files) to run the simulations. To use the analysis framework with Asset Score, the framework was extended to operate on XML files as well as OSM files and EnergyPlus IDF files. Fig. 3 shows the workflow for running simulations with the Simulation Framework and XML file injected. An XML file was generated for each seed model which was then analyzed using the OpenStudio Analysis Framework.

The OpenStudio Analysis Framework relies heavily on the use of OpenStudio measures [3]. In the simplest terms, a measure is a small Ruby script that is executed against the input file to make a controlled change. These changes can be simple perturbations (e.g., change the chiller coefficient of performance to 5.0) or can be quite complex (e.g., add two stories to a building while maintaining the same square footage). For the Asset Score analysis, the concept of measures was extended to enable the perturbation of the Simu-



**Fig. 3.** Workflow for running XML-based measures using the OpenStudio analysis framework.

ation Framework's XMLs. The Asset Score used a combination of XML measures (which manipulated the Preview Simulation Framework's XML file), OpenStudio measures and EnergyPlus measures. These measures are collectively applied to the XML file to generate an EnergyPlus file that is simulated to generate simulation results. The reporting measure component then takes in the SQLite output generated from EnergyPlus to post-process the data and generate results required for the development of the regression model.

### 3.3. Sampling and stock simulations

Each seed model contains up to 38 input variables, representing various building system inputs analyzed by the Asset Score Tool. Each variable was assigned a minimum, maximum, mean, standard deviation and distribution (i.e., uniform or triangle) representative of typical efficiency ranges based on existing building stock and available advanced technologies. Defaults in a seed model (e.g., floor plan area, number of stories, envelope U-factor, HVAC system efficiencies) are assumed to be the mean values for that building type. The input variables were individually modeled without accounting for interactive effects. The list of input variables and their default values and ranges are discussed in a previous publication [1].

The dependent variable, i.e., the output of each simulation run, is the adjusted source EUI calculated from modeled site EUI based on fuel mix (electricity, natural gas, district steam, etc.) after climate normalization. Adjusted source EUI was calculated by first multiplying the fuel type totals by nominal source-to-site ratios [17]. The second adjustment was climate normaliza-

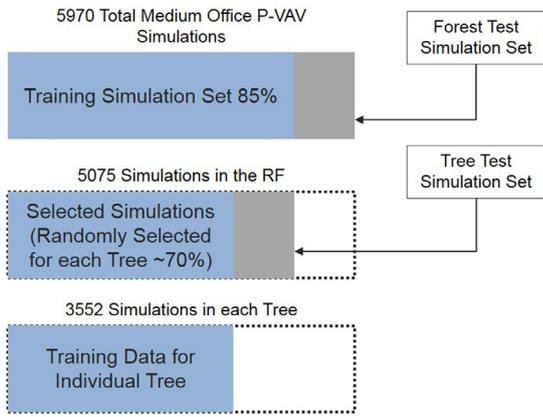
tion, which is intended to generate comparable scores across climate zones. Over 1000 sets of climate coefficients were developed to adjust building energy use at the end use level. Each set of coefficients includes multipliers for heating, cooling and fan energy use for the corresponding weather station. Climate independent loads, such as lighting and plug loads, are not adjusted. The weather coefficients were derived from simulations of nine prototype buildings of different use types and HVAC types across 1020 weather stations in EnergyPlus. The source EUI values (by end use) were then adjusted by multiplying a set of coefficients developed for each weather location. The methodology of climate normalization is discussed in a previous publication [18]. The adjusted source EUI was calculated for each simulation result, and was the only dependent variable used in training the regression models.

To create the uncertainty models, approximately 8000 variations of an individual seed model were simulated using the OpenStudio Analysis Framework. The variations of the seed model were derived by randomly sampling each of the 38 input variables. This framework allowed for the specification of ranges of allowable values as well as the distribution of these ranges. Input variables were defined as multipliers from the mean values in the seed model. This allows for the same analysis configuration to be used for all of the seed models. After all the allowable ranges and associated distributions were defined, a Latin hypercube sampling algorithm was used to create the sample set of values for the simulations. These samples were drawn from distributions determined through extensive interactions with industry expert working groups. The algorithm and its efficacy in developing energy models are discussed in [19]. Results from the initial simulation process consisting of 13,600 analyzed sensitivities can be accessed from [www.dencity.org](http://www.dencity.org), the website for the DOE's Energy City [20]. The number of simulations chosen was based on training regression models to an increasingly smaller subset of the 13,600 simulation datasets, until a loss in accuracy of the regression models was observed, slightly below 8000 simulations.

### 3.4. Developing regression models

Multiple regression techniques were initially investigated to determine an acceptable technique for use in meta-modeling for the previously detailed datasets. In this paper, meta-modeling is defined as a regression model in addition to the input and output processing required to allow a non-technical user to execute the regression algorithms. Based on past institutional experience with using linear regression models for similar purposes, non-linear regression models were the major focus of exploration for this analysis. Further exploration found that allowing support vector machines to accurately regress across different climate zones [21,22], would require significant tuning and effort. Although convolution neural nets may have performed exceptionally well on these datasets, the random forest approach was chosen due to the simplicity of its implementation and its robustness, as well as its generally excellent performance, as discussed below. For details of the random forest model, refer to [23]. All methods were tested in R, using the packages randomForest [24,25] and gam [26]. Throughout this section and several following, results from the Medium Office (packaged rooftop VAV with electric reheat) seed model will be shown to illustrate the workflow.

To create the regression models for each seed model, the ~8000 data points were randomly divided into two sets: a training set comprising 85% of the data used and a test set comprising the remaining 15%, which would be used to measure the accuracy of the regression model. See the top pane of Fig. 4. The training simulation set was then passed to the random forest generating algo-



**Fig. 4.** Regression model training process based on 8000 simulation runs per model generated.

rithm, contained in the R package Random Forest, as illustrated in the middle panel of Fig. 4. A random forest is a large aggregation of decision trees, each of which is independently trained. Each tree is given at random 70% of the data provided to the forest, on which it then regresses. An individual tree is represented in the bottom pane of Fig. 4. The remaining 30% of the data points seen in the middle pane are used by the random forest to measure the accuracy of each tree once it is built, and aggregated to provide an estimate of the accuracy of the forest ensemble. At the time of the analysis, only two hyper-parameters were available in the R package for tuning the performance of the random forests,  $m\_try$  (the number of variables to test at each split) and  $n\_trees$  (the number of trees to build in the forest.) Two separate processes were executed to choose the parameters. In the first, multiple models were built with increasing numbers of trees within the forest and cross validated. In this experiment, the accuracy of the forest was determined to have converged by 200 trees, which was adopted as the default value. The second experiment was to perform a gridded search across  $m\_try$  and  $n\_trees$  both. This search demonstrated that the default  $m\_try$  value of  $n/3$ , where  $n$  is the number of features in the parameter space, provided the best cross-validation score in the search space, and that the accuracy of the forest had converged by the selected parameters against the reserved test set.

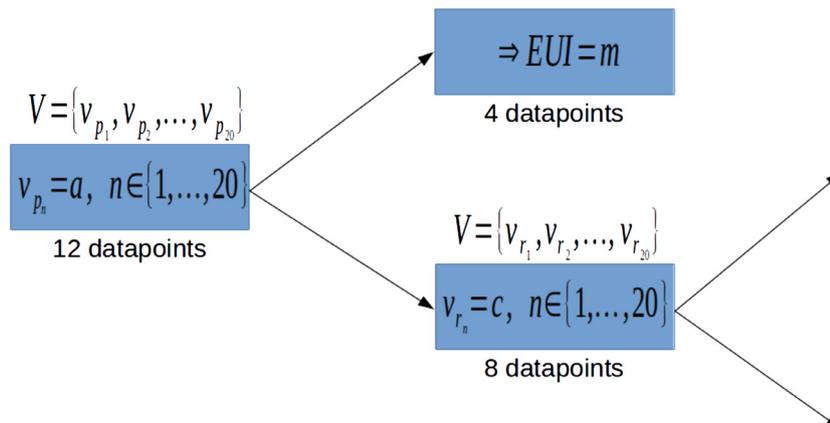
To create the tree, each node considers half of the explanatory variables, selected at random. The node must divide all data points associated with it into two groups around a splitting value selected along one of the considered explanatory variables. This splitting value is selected to minimize the variance of the new nodes

created by the division, using the mean square error of the two daughter nodes as a proxy. The mean square error is defined as the sum of the variance and the squared bias—in case of an unbiased estimator, this is equivalent to the variance. It can be calculated as:

$$\sqrt{\frac{1}{n} \sum_{i=1}^n \left( S_i - \frac{\sum_{j=1}^n S_j}{n} \right)^2}$$

where  $S$  is the set of sample observations, i.e., simulations, to be evaluated at a given node, and  $S_n$  represents the  $n$ th simulation result. Note that the assumed truth is the average of the set of observations, i.e.,  $\frac{1}{n} \sum_{j=1}^n X_n$ , as the value returned from an exit node in the tree is the mean of the observations contained in the node. This approach is also used with categorical variables (i.e., climate zone), which are ordered and mapped to the integers arbitrarily. Although this is a serious drawback to the algorithm's implementation, changing this behavior was outside the scope of this project. As illustrated in Fig. 5, this process continues until each node has five or fewer data points associated with it. In that case, the branch is terminated and the average EUI of the remaining data points is set as the exit value of that branch. For further details regarding the process by which an individual tree can be constructed, refer to [9,23]. When this process has been completed for each tree in the forest, the training of the regression model is complete.

The final step of the regression model generation process is to judge the accuracy of the random forest. Although the forest keeps internal accuracy statistics, which are inherently robust, the 15% of simulation data reserved (see the top pane of Fig. 4) is used to gauge the overall effectiveness of the regression. To do this, the EUI values of the test dataset are predicted by the regression model using only the explanatory variables. The returned predictions are compared with the known truth values and the resulting graph, commonly called a parity plot, is saved to file for each regression built. This plot can be seen in Fig. 6 for the Medium Office packaged variable air volume (PVAV) with electric reheat seed model. There is a high fidelity goodness of fit between the predicted and simulated values, with an  $R^2$  value of 0.935, on the low end of  $R^2$  values seen across the project. This shows that the regression model provides a high degree of accuracy in predicting simulation results within the defined sample space, at a fraction of the computational time of a full building energy model (BEM). In addition, it is clear from Fig. 6 that the prediction engine slightly over-predicts low EUI structures, and slightly under-predicts high EUI structures. This trend was seen across the majority of engines, regardless of building type and HVAC system type.



**Fig. 5.** Node splitting procedure for the random forest training algorithm.



Fig. 6. Parity plot showing the fit of the reserved test data of 1194 data points against the predicted values of the regression model.

#### 4. Integration of regression model with preview

The regression models were integrated with the Asset Score Tool as a Preview function. User input, both values and certainty, is passed to the meta-model through the AS XML. This XML contains the FEDS inference engine's best guess of various values that are not user inputs (such as wall U-factor, window U-value and solar heat gain coefficient), as well as a Boolean value representing the user's certainty for each of the Preview default values. These values are parsed out of the XML and used to populate the regression model. To capture the uncertain nature of the user's inputs, the meta-model takes the information provided by the user and uses it as a basis for sampling the regression model. Depending on the user's certainty in their information on different end-use categories, the respective sets of variables are either fixed (if a value is verified by the user), sampled over a triangle distribution centered at the user's input (if a value is indicated as unknown by the user), or sampled uniformly. This last procedure is only employed by default on controls variables and geometry configuration variables. HVAC variables, should the user be unsure of their HVAC system type, are also set to uniformly uncertain.

Given the limited input of the Asset Score Preview, the geometry variable groups of the XML, as well as all control strategies, are always set to be uncertain. The Asset Score XML certainty inputs are parsed in one of three ways. If the user indicates they are certain regarding a variable group, then the values for that group are fixed for all 10,000 data points. In the case that the user indicates they are uncertain about a variable group (excluding HVAC), the values inferred by the Analytical Engine are used as the modes of a set of triangle distributions spanning the entire range of each variable in the variable group. See Figs. 7 and 8 for an example (non-HVAC) unspecified variable.

If the user fails to specify the HVAC system, there is a great amount of uncertainty in the model. One option considered was to run the uncertainty analysis on multiple HVAC system types. This was ultimately not selected as the course of action as it would in

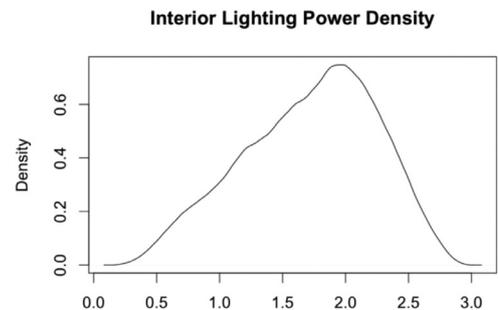


Fig. 7. Input distribution for interior lighting power density with an inference of  $2 \text{ W/ft}^2$  and uncertainty distribution.

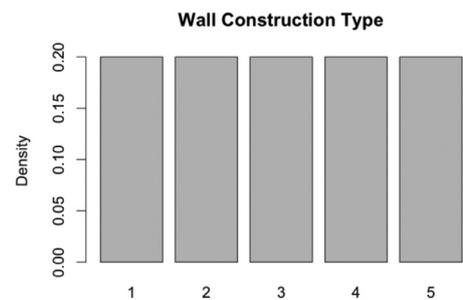


Fig. 8. Input distribution for wall construction type with values for an uncertain input.

many cases return an extremely wide score range, thus providing no useful information. Instead, it was decided that in the case of an unspecified system, the default HVAC system type (based on CBECs data and prototype buildings) would be used; however, all HVAC-related values, such as the system efficiency, controls and fuel type, would be considered uniformly uncertain across their entire range. Due to the importance of several of these variables, this will pro-

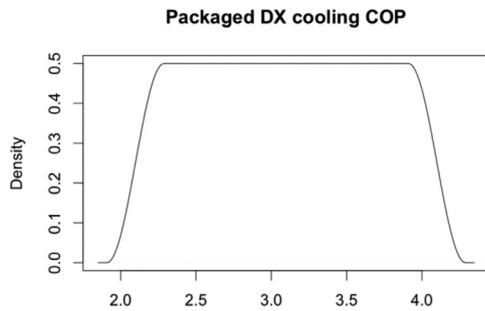


Fig. 9. Input distribution for a variable in the HVAC group, for an uncertain input.

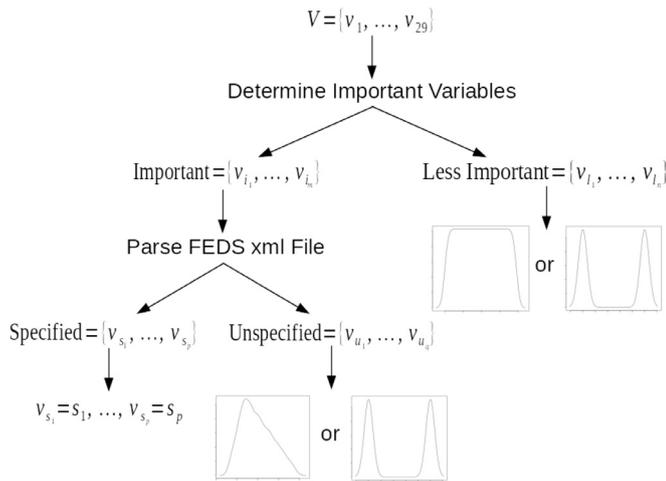


Fig. 10. Variable importance specification process, showing the bifurcation of variables based off of the variable classification (controls, geometry, HVAC, etc.) user input and FEDS inference.

duce a sufficiently wide EUI range, but one that still provides the user with some value. Fig. 9 gives an example of the distribution of an uncertain HVAC system variable. In the case of a categorical variable, i.e., wall construction type, if the input is not certain, all possible values are uniformly sampled.

The process by which variables are assigned distributions is summarized in Fig. 10. All controls and geometry variables, as well as HVAC variables (if the user is uncertain of system type), are determined to be unimportant for user input in the Preview tool, and sampled uniformly across their range. All other variables that are not marked as certain by the user are assigned triangle distributions spanning the variable's range with a maximum at the FEDS indicated value if they are numeric, or assigned a uniform distribution if they are categorical. Finally, all values specified as certain by the user are fixed at that value in all additional sampling, once again generated using a Latin hypercube sampling algorithm.

#### 4.1. Impacts of uncertain inputs

The results of the regression model are highly dependent on the user's certainty of input. Fig. 11 shows the distributions returned from a base medium office AS XML that sampled against the medium office (packaged VAV with electric reheat) seed model. By default, each estimate is made up of 10,000 samples drawn from the distributions determined based on the process discussed above. Four different certainty sets were used for predictions. In the first case, all certainty types (except geometry, which is always uncertain) were set to certain. In the second case, only HVAC system type and fuel type were set as certain, in the third case, only lighting inputs, including lighting power density and lighting con-

trol, were set as certain, and in the last case, none of the parameters were set as certain. As shown, the regression model is highly sensitive to the certainty of the inputs. Particularly desirable is that the mean, mode and range of the distributions are highly articulated, allowing simple statistical measures to provide a high degree of information to the user. The adjusted source EUI as modeled by EnergyPlus was 185 kBtu/ft<sup>2</sup>-yr (2100 MJ/m<sup>2</sup>/yr), which falls in the middle of and is approximately the maximum likelihood estimation of the all certain distribution.

An additional challenge faced in the development of the preview methodology was the support of the full Asset Score Tool for ASHRAE 90.1 Appendix G system types [15], across all Asset Score building types [4]. Given 8000 required simulations per combination of building type and system type, a full set of input data would have required approximately 1.4 million simulations. At the time, running more than 250,000 simulations using the OpenStudio Analysis Framework was challenging, although this limit has since been significantly raised. Therefore, a subset of the full 176 possible combinations of system and building type had to be selected for simulation, and the remaining combinations mapped to a regression model. The system types were selected based on the most predominant system types found for each use type, as identified through CBECS [27] data. For the less predominant system types, a mapping was developed to a similar system analyzed. A subset of this mapping can be found in Table 2. In total, 43 combinations of system type and building type were simulated and used for regression models in this project. For example, analysis of CBECS data for libraries showed that only 16% of all libraries used VAV systems and 2.7% of all libraries used heat pumps for heating and cooling. Packaged air conditioning systems were used in 47.9% of the libraries. Hence, the three seed models created for the library use type were defined using packaged air conditioning systems, VAV with electric reheat and VAV with hot water reheat. Heat pumps were not analyzed for libraries. Similarly, CBECS data showed that only 7% of retail buildings use VAV systems, whereas 18.5% use individual air conditioners and 45.2% use packaged air conditioning units. Hence, VAV systems were not analyzed for retail buildings, and instead packaged terminal equipment and rooftop units were analyzed. Table 2 shows this mapping for a subset of use types.

#### 4.2. Result post-processing

The regression model gives an estimate of the EUI range (within 95 percentile of results) as well as the mean EUI for the building with all the input values and associated uncertainties. The minimum, mean and maximum of the distribution of values from the regression model is written as a CSV file and returned as the output of the meta-model. The minimum, maximum and mean EUI values are mapped to Asset Scores. To fit the distribution to the desired score range, a simple mapping is used. Let H be defined as the high Asset Score, L be defined as the low Asset Score, M as the mean Asset Score and S as the desired Asset Score range. Then the lower limit of the range,  $S_{min}$ , and the upper limit of the range,  $S_{max}$ , is given by:

$$S_{min} = M - S_{range} \frac{M - L}{H - L}$$

$$S_{max} = M + S_{range} \frac{H - M}{H - L}$$

This method ensures that tails and skewness are well represented in the Preview Asset Score presented to the user. Note that the desired score range is fixed for varying uncertainty conditions to ensure a consistent user experience with Preview report, although more uncertain values yield a wider score range.

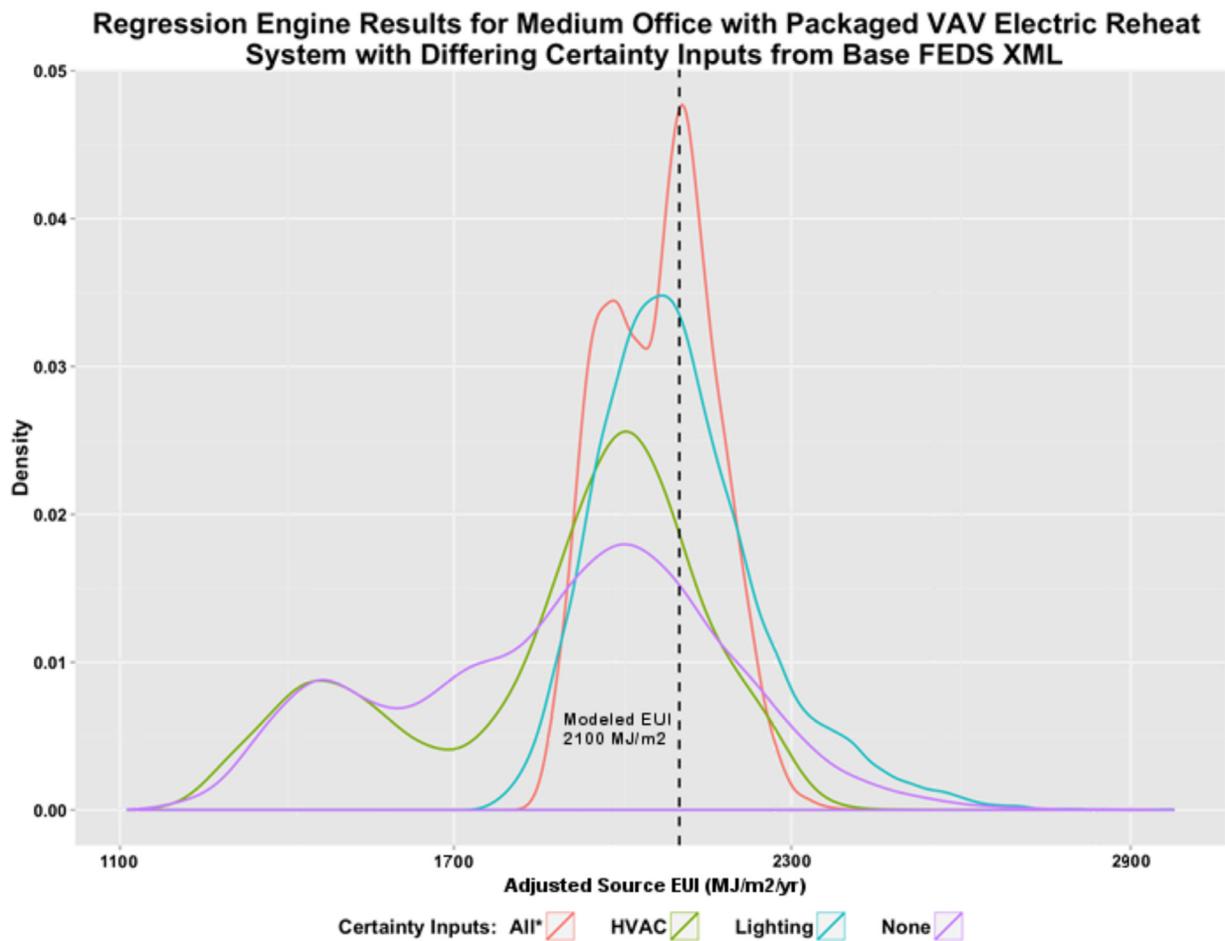


Fig. 11. Example of the impact of specifying various levels of uncertainty in the input to the analysis. Each distribution is based on 10,000 pseudo-random samples.



Fig. 12. Example of the score range returned from the analysis.

An Asset Score Preview report is generated, which provides the current score range, potential score range and estimated source energy savings, see Fig. 12. The estimated savings are based on the dataset of buildings entered into the Asset Score Tool and average savings seen by buildings scoring within a certain range. The potential score range is calculated based on the EUI reduction after the savings are applied. It is worth noting that building the regression models can be relatively time-consuming, on the order of 2–10 min per regression model; however, executing the built regression models is very fast, taking around 10–100 ms, allowing for near-real-time feedback to the user.

### 5. Testing and validations

The meta-models were tested using two sets of inputs: (i) the seed models (i.e., simplified Prototype Buildings) developed for the uncertainty analysis, and (ii) buildings entered by users into the Asset Score Tool during the pilot studies conducted in 2012 and 2013 [28]. The intent of this testing process was to determine if the

uncertainty analysis model could accurately reflect the efficiency of a building, considering the limited data provided.

The seven basic building characteristics of the 22 seed models were entered into Preview to generate the score range for each seed model. The complete set of building characteristics for the seed models was entered into the full Asset Score Tool to generate the Asset Score using whole building energy simulation. The acceptance criteria employed in the testing process required the full Asset Score to be within the range returned by Preview. All buildings passed the test as the actual scores lie within the score range determined through Preview. Table 3 shows the example results. Building geometry and HVAC system controls, such as demand control ventilation, supply temperature reset, and others, are always considered uncertain. This can have a significant impact on how a full building scores in reference to the Preview score range. The fact that some seed models score closer to the Preview high score and others closer to the low score is a result of the sensitivity of the applicable HVAC system controls. For example, the medium office seed model is analyzed with a packaged VAV with electric reheat system with controls such as fan static pressure reset and minimum airflow fraction specified at 0.3. The Preview model assumes these HVAC controls to be uncertain and the EUI range determined includes the impact of a minimum airflow fraction specified at 0.4 and 0.3 as well as the VAV fans modeled with and without static pressure reset controls. The full seed model is run with a minimum airflow fraction of 0.3, resulting in lower reheat energy relative to 0.4, and thus a score that is closer to the Preview high score value.

**Table 2**  
Matrix showing mapping of HVAC system types across building types.

System type	Modeled system for the given building type and system type				
	City hall	Courthouse	Education	Library	Retail
System type 1	Packaged terminal air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged terminal air conditioner
System type 2	Packaged terminal heat pump	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop heat pump	Packaged terminal air conditioner
System type 3	Four pipe fan coil unit	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged terminal air conditioner
System type 4	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner
System type 5	Packaged rooftop heat pump	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop heat pump	Packaged rooftop air conditioner
System type 6	Packaged rooftop VAV with hot-water reheat	VAV with hot-water reheat	Packaged rooftop VAV with hot-water reheat	Packaged rooftop VAV with hot-water reheat	Packaged rooftop air conditioner
System type 7	Packaged rooftop VAV with electric reheat	VAV with hot-water reheat	Hot-Water Reheat	Packaged rooftop VAV with hot-water reheat	Packaged rooftop air conditioner
System type 8	VAV with hot-water reheat	VAV with hot-water reheat	VAV with electric reheat	Packaged rooftop VAV with hot-water reheat	Packaged rooftop air conditioner
System type 9	VAV with electric reheat	VAV with hot-water reheat	VAV with electric reheat	VAV with electric reheat	Packaged rooftop air conditioner
System type 10	Warm air furnace	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner
System type 11	Ventilation only	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner	Packaged rooftop air conditioner

**Table 3**  
Test results for the SEED models.

Seed model	Preview low score	Preview high score	Full input mode score
Medium office	3	6	5.5
Retail stand alone	6.5	9.5	7
Warehouse	5.5	8.5	8
Small office	4	7	6
Large office	4.5	7.5	4.5
Primary school	5.5	8.5	6
City hall	3.5	6.5	5.5
Courthouse	5.5	8.5	6.5
Library	6	9	7
Small hotel	7	10	8
Large hotel	7	10	8.5
Assisted living	6	9	7
Medical office	4	7	5.5
Mid rise apartment	6.5	9.5	7.5
High rise apartment	5	8	7.5
Low rise apartment	6.5	9.5	6.5
Police station	4.5	7.5	5.5
Post office	4.5	7.5	5
Parking garage (Heated/Cooled)	5	8	6.5
Religious building	5	8	5.5
Senior center	5	8	7
Community center	4	7	6

The pilot buildings were evaluated with two configurations: the minimal seven inputs with all Preview defaults marked unknown and the seven inputs with all defaults being edited or verified based on the actual building data. The first set, submitted with seven inputs and none of the default inputs verified, did not consistently result in score ranges that included the actual scores. Of the 160 pilot buildings that were analyzed for this purpose, 65% had scores within the range identified by Preview and the remaining 35% scored outside the resulting Preview range. The alignment was dependent on how closely the preview defaults coincided with the actual values as well as the sensitivity of the parameters that did not coincide. Editing or verifying the default values to actual values significantly improved the alignment of the buildings analyzed.

A subset of 40 pilot buildings were randomly selected and entered in Preview with the seven minimal inputs and default values modified in accordance to the actual building inputs. In this analysis, the default values for lighting fixture types, HVAC system type, window glass type and window-to-wall ratio were either verified or edited to reflect the actual systems present in the building. A higher degree of accuracy was observed where the actual score of the building fell within the score range calculated through the regression models for 95% of the test cases. Buildings falling outside the Preview score range were the highly efficient buildings with equipment performance ratios higher than typically found. Since equipment efficiencies, inferred by the Asset Score Analytical Engine, are based on CBECS data, these buildings were not well represented and the full score was much higher than the preview score. Fig. 13 shows the example results of buildings tested in the second configuration. The X axis is the ID of the building entered in Asset Score Tool and Y axis is the score. The HVAC system type, lighting power density and the window-to-wall ratio were sensitive inputs that were found to affect the uncertainty analysis. Measuring this sensitivity reliably remains an open issue, making these insights qualitative in nature. Generally speaking, as seen in the results in Fig. 13, the accuracy of the Preview score is significantly improved when these three inputs are validated.

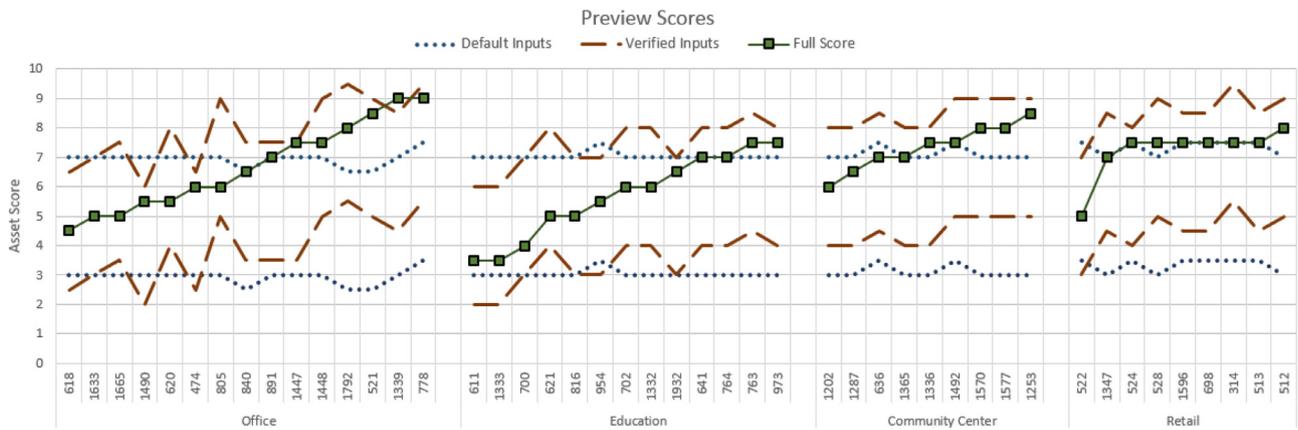


Fig. 13. Testing results for pilot buildings.

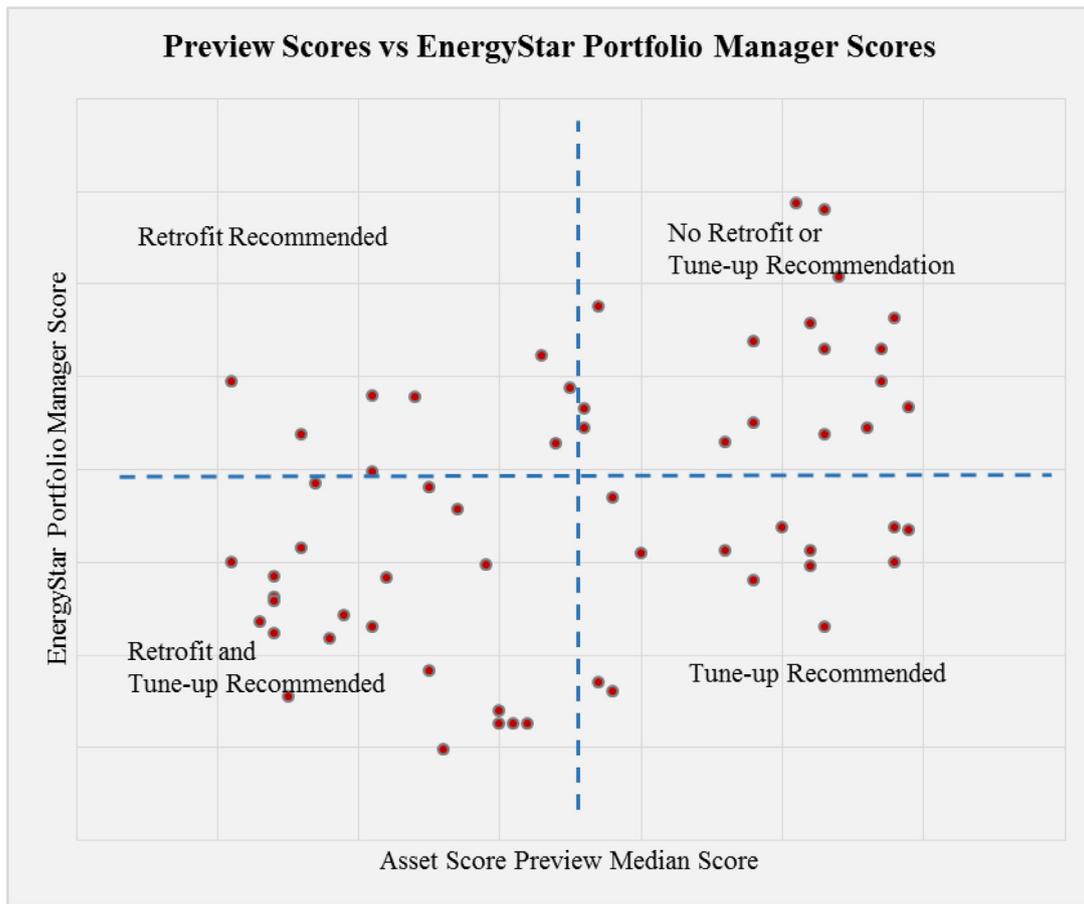


Fig. 14. Quadrant matrix analysis for overall building performance.

## 6. Applications

Asset Score Preview provides a simplified approach for batch analysis of a large number of buildings to identify buildings with the highest potential for energy savings. Preview assessment is also beneficial when compared to measured energy use data or benchmarking score, such as ENERGY STAR Portfolio Manager score [29]. When compared to Portfolio Manager scores, Asset Score Preview scores provide supplemental information to identify opportunities for energy efficiency measures by giving a multidimensional view of a building's performance. On one hand, the Portfolio Manager

score provides insight into a building's operation; conversely, Asset Score Preview can highlight a building's asset performance.

Fig. 14 provides an example of the quadrant analysis approach for comparison of a dataset's Portfolio Manager Score against Asset Score Preview's median score. The dashed lines show average values for both the Portfolio Manager scores and Asset Score Preview datasets. Buildings with high Portfolio Manager scores and high Preview scores are most likely to have the least possibility for retrofits or system tune-ups versus buildings with both low Portfolio Manager scores and Preview scores. This quadrant analysis approach is being utilized by several organizations for screening

buildings with highest energy savings potential through retrofits and system tune-ups.

## 7. Conclusions

The Asset Score Preview creates a viable framework for analyzing building efficiency. With limited effort from users, it can provide useful information about a building's assets and identify buildings that have great potential for improvement or could benefit from a more in-depth analysis. The use of random forest models to ascertain the range of uncertainty in the building's EUI allows limited inputs from the user to generate meaningful results without the significant computation time and power required for more detailed whole building energy modeling. The validation of this framework shows that additional sensitive inputs verified by users can greatly improve the accuracy of the Preview results. Buildings with more complex geometry, mix-used type, or advanced HVAC systems may not be suitable for Preview because oversimplification likely results in low accuracy.

This study explores a feasible way to increase the adoption of a rating system by offering a more friendly entry to the full capabilities of the Asset Score. Preview is intended to provide an easy, streamlined approach for quickly screening and evaluating building efficiency with limited available information. The balance between input simplicity and result accuracy is a constant battle. Preview is seeking this optimal point. The score range estimated through Preview is intended to indicate a building's general energy efficiency. The capability of converting a Preview building to a full Asset Score building allows the Asset Score Tool and associated energy efficiency analysis to be more accessible to a broader range of users.

To facilitate analysis of a large number of buildings, Preview also supports batch analysis, which allows users to upload a group of buildings through a spreadsheet and generate Preview scores all at once. The batch-analysis workflow includes a simple three-step process of spreadsheet upload, batch simulation for the uploaded buildings and a CSV download with score ranges of all buildings. The intent is to provide a capability for organizations looking to conduct analysis on a large number of buildings in order to identify buildings for more detailed review. The batch analysis capability reduces the amount of manual work required to generate the Preview scores and can be used to pre-analyze large portfolios of buildings with relatively minimal initial effort. The expected users include utility program administrators, city energy program managers and large real estate portfolio managers.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.enbuild.2018.06.041](https://doi.org/10.1016/j.enbuild.2018.06.041).

## Appendix A

Table A.1.

**Table A.1**  
Variables analyzed for preview regression model development.

Variables	
Air handler fan efficiency	Interior lighting power density
Aspect ratio	Location
Chilled water reset	Minimum airflow fraction
Chiller pump control	Orientation
Condenser pump control	Perimeter zone depth
Cooling efficiency	Roof construction type
Cooling tower control	Roof U-value
Daylighting control	Shading height above window
Demand control ventilation	Shading projection factor
Economizer	Gross floor area
Energy recovery ventilation	Supply air temperature reset
Fan control	Wall construction type
Fan static pressure reset	Wall U-value
Floor plate area	Water heater efficiency
Floor R-value	Window solar heat gain coefficient
Floor-to-ceiling height	Window sill height
Floor-to-floor height	Window U-value
Heating efficiency	Window visible light transmittance
Heating fuel type	Window-to-wall ratio

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