Where HVAC models fail - a conceptual framework for extending effective HVAC modelling into early concept design of net zero buildings

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Abstract
The scope and scale of performance objectives for building design have increased under net zero paradigms; however, the significant influence of HVAC system strategies and the role of uncertainty often remain unaddressed in early stages. This study presents a preliminary framework for incorporating intuitive abstract representations of often complex mechanical systems through functional decomposition and component-based surrogate modelling, while preserving connections to high fidelity simulation schema for scalability and technical diagnostic capabilities. An illustrative case study implements the framework for heating demand in a medium office, demonstrating computationally efficient tracing of uncertainty through interpretable VAV system transformation components.

Key Innovations
• Describes a conceptual framework for application of functional decomposition to identify core load components and transformations relevant to early stage building performance modeling
• Identifies characterization and assembly methods to connect to detailed HVAC simulation and schema
• Applies surrogate modelling to encapsulate component transformations, supporting modularity and efficient computation of a broader design space, with scalable granularity
• Provides an example of intuitive, high-level design space exploration with uncertainty analysis through the use of interpretable surrogate components

Practical Implications
Practitioners should incorporate HVAC modelling earlier in the design process – with consideration of a broader set of performance metrics and design options – using high-level, but systematic decomposition techniques and methods that account for uncertainty

Introduction
Academic literature has highlighted the value of building performance simulation in early design decision-making, with emphasis on the need for computationally efficient, accessible exploration of the vast problem space (Østergård et al., 2017). Early design decisions can have impacts on cost and performance that are compounded by time, and opportunities for beneficial integrated design approaches may become infeasible if only considered during later stages of design and construction.

Mechanical design elements in particular can behave non-linearly, featuring discontinuities and multi-modal behaviour. Mechanical system design and control is integral to design decision-making tied to capital and operating costs, emissions targets, and geographic or climatic differences. The complex interactions of mechanical systems can amplify uncertainty in ways that significantly alter the characteristics of the design space. Relevant analysis is uncommon in the earliest stages of concept design development, where decisions would entail understanding complex interactions and discrete changes, and conventional detailed analysis would be time-consuming. As a result, this is also an area where there is a high potential for saving time, cost and improving practical application of building simulations.

A number of studies have identified that sensitivity to uncertainty in HVAC parameters is among the most significant for determining building energy performance (Coakley et al., 2014), and yet representations of HVAC in design stage research models typically use basic templatized implementation, contrasting counterparts in detailed calibration research and professional practice (Kim et al., 2016). For example, certain HVAC assumptions often use ‘typical defaults’ (e.g. start-up controls, sensor placement, etc.) or broad generalizations (e.g. whole building system boundaries) which may have significant influence on performance under diverse or irregular load conditions.

Furthermore, while energy is still the dominant objective in building modelling practice, the scope of application for BPS has extended to encompass a wide variety of building functions and performance requirements, with rapid growth in the variety, breadth and depth of software available to evaluate social, environmental and financial objectives, or to provide narrow analysis in specific sub-domains (Augenbroe, 2019).

Simulation in practice still tends to be evaluative rather than proactive, which contrasts the priorities of early designers seeking to apply BPS for decision-making (Østergård et al., 2017). A paper from de Wilde (de Wilde, 2017) also emphasizes the need for more efficient global design space exploration, rather than optimization or evaluating one-at-a-time design options. Clarke (Clarke & Hensen, 2015) proposed an ideal workflow for BPS that
involves iterative refinement drawing more from shared knowledge resources and statistical methods.

BPS research is active in a wide variety of sub-fields, with progress towards refined methods and tools sometimes developing in insular regions of the problem space. The opportunity for transferring knowledge and connecting methods is significant.

**Performance-based Modelling**

Performance requirements are measures of how well a system satisfies a function (whether of quality, resource efficiency, or work-load capacity; timeliness or readiness) (Gilb, 2005). It encompasses all building functions, including occupant comfort, health, safety, economic productivity, environmental, ecological, and technical resiliency. A white paper from de Wilde (de Wilde, 2017) argues that any framework for assessing building performance should take this broader scope into account, and that research in this area often lacks critical reflection on the challenges inherent in this perspective.

Integral to a Systems Approach are the processes of functional decomposition and systematic re-assembly of modelled components to fit the problem space (Gilb, 2005). Both de Wilde (2018) and Augenbrue (2019) suggest such an approach in their re-structuring of the over-arching BPS framework. Their goal is to connect functional building “performance requirements” to modelled “system aspects” (assembly of building elements that perform the function). The implications of this in research and practice are largely unexplored.

**Modelling Challenges and Failure**

The credibility and reliability of BPS in practice has been challenged by the presence of a “performance gap” that exists between simulated and observed results (de Wilde, 2014). A review of the performance gap for compliance modelling in a regulatory context provided a detailed breakdown of sources of error, including longitudinal factors, and found very large variations in their magnitude (-10% to 67%, depending on building type) (van Dronkelaar et al., 2016). Sources of error can be traced through the various stages of a building’s life-cycle.

Robinson (Robinson, 2008) describes the goal of conceptual modelling as to keep the model as simple as possible, while satisfying the objectives of the simulation study. A summary of the challenges facing the use of BPS to support design are described in a number of reviews of the field (Clarke & Hensen, 2015).

Pervasive equifinality in BPS (where the same outcome can result from a variety of constituent parameter combinations) poses a significant challenge in decomposing and re-assembling sources of error in practice in the face of environmental, workmanship and behavioural uncertainty. This under-specification problem can be further exacerbated with the use of black-box modelling methods during early stages of design (both of which entail elevated uncertainty); however, there is potential to leverage lessons learned from other sub-disciplines that can be explored (de Wit & Augenbroe, 2002).

There is a growing concern that traditional simplified BPS methods and tools are not capable of handling the increasing demands of net zero building energy objectives, expectations for performance across holistic environmental criteria and sophisticated building systems and controls (Hong et al., 2018).

A paper by Clarke (Clarke & Hensen, 2015) suggested that simulation should primarily be considered learning support, rather than a design generator or optimizer. The aims of BPS are for high integrity representation (capturing sufficient complexity), coupling of different domains (capturing interactions and conflicts between component parts), and design process integration (handling diverse objectives and workflows). Reliability and usefulness of models can be derived from transparency and interactivity; providing tools and controls that allow domain experts to interrogate and understand the problem space, including unknowns and sources of potential error (Østergård et al., 2016). Reconciling good modelling practice in this context implies the need for modular, scalable tools that provide sufficient accuracy to support qualitative objectives.

There is a gulf of opportunity to be bridged by developing a framework that provides intermediate, transitional, transparent understanding between high level abstractions and detailed models that integrate uncertainty. This is a failure of not realizing the full potential of BPS. This is perhaps most egregious with regards to mechanical systems. For example, ASHRAE 209 introduces HVAC decision-making in “Modelling Cycle #4” as a small set of arbitrary options, after concept modelling and load reduction decisions have been made.

**Uncertainty**

Clarke (Clarke & Hensen, 2015) has argued that reporting confidence intervals and capturing uncertainty needs to become standard practice. Aleatoric and epistemic uncertainty are present in each of the following types (Wate et al., 2020):

- Modelling (structural) uncertainty
- Numerical uncertainty
- Specification (parameter) uncertainty
- Scenario (statistical) uncertainty

Distinguishing the portion of uncertainty attributable to error is also useful (de Wilde, 2014):

- Heuristic Error
- Measurement Error

**HVAC Modeling**

Some preliminary work has shown promise decomposing HVAC systems into constituent elements, most often based on sensitivity analysis for model order reduction through simple elimination; however, some research has taken the next step to re-combine components as part of a modelling framework, including by zone and measure (Yang & Becerik-Gerber, 2015), “intermediate parameters” based on aggregation (e.g. end-uses) (Eisenhower, O’Neill, Fonoberov, et al., 2012), or
generalized “macro-parameters” (Calleja Rodríguez et al., 2013).

Further reviews of detailed HVAC system simulation methods highlight the benefit of component-based modelling approaches that include abstraction, generalizable frames of reference and uncertainty analysis for adequately evaluating alternative system configuration and control strategies, and for investigating innovative technologies (Trcka & Hensen, 2010).

There is active research into techniques for detailed model calibration (“digital twins”), uncertainty analysis, and extension to a broader interconnected network (e.g. the “Internet of Things”), including as part of fault detection and diagnosis (FDD) and Model Predictive Control (MPC) (Fabrizio & Monetti, 2015). A recent comprehensive review of MPC explored bottom-up schema and advanced equations-based methods, while noting the lack of applications in real practice despite potential to save 13-28% of operational energy consumption (Drogha et al., 2020).

However, few high-level parametric studies consider HVAC. The reasons for this include the challenges of incorporating probabilistic representations of discretized, non-linear HVAC design parameters into detailed baseline models (Ruiz & Bandera, 2017). There is a significant disconnect between building energy modelling research for operational stage (controls, calibration, etc.) and early stage design, which provides untapped opportunity for knowledge transfer.

**Surrogate Modelling**

Surrogate modelling is an active area of research in BPS as it is situated at the intersection of advancements in machine learning, greater emphasis on parametric design space exploration and access to more computational resources. Surrogate modelling involves training statistical meta-models based on BPS input and output data (Eisenhower, O’Neill, Narayanan, et al., 2012). They represent an equivalent problem space to the original BPS definition, but can be evaluated significantly more efficiently, opening up potential for rapid Exploratory Data Analysis (EDA). Different machine learning approaches have yielded various levels of accuracy and interpretability, with reliable results shown for well-defined Deep Neural Nets, Boosted Decision Trees, and Gaussian Processes (Westermann & Ewins, 2019).

**Component Surrogate Modelling Approach**

A promising area of study that might alleviate some of the problems inherent in black box modelling involves the combination of component meta-models into ensemble surrogates; however, only a handful of studies have attempted this approach for buildings. A paper by Geyer (Geyer & Singaravel, 2018) compared a monolithic model to a components-based implementation that used neural nets to represent elements in the enclosure systems of a generalized zone.

Extending this approach to whole-building modelling and HVAC systems is promising and unexplored. Integrating a framework for decomposing and defining the components lends greater benefits, such that:

- the models can be modular and scalable for generalizability,
- system aspects can be aligned with building functions and performance requirements to maintain interpretability and usefulness,
- uncertainty can be traced and quantified to support accuracy and validity

Functional analysis focuses on the flow of inputs and outputs to characterize constituent sub-functions or components of the system. The goal of performance-based functional decomposition is to isolate functional units that can map performance indicators (metrics for performance requirements) to system aspects (representative of corresponding technical model components).

A key objective of this component modelling approach is to provide domain experts with access to the key diagnostic information that they need to compare results to expected outcomes and gauge validity, supporting existing workflows and more interactive engagement.

Traditional BPS in practice can be an opaque process generating generic outputs, often with limited capacity for iterative feedback or refinement. Based on a version of BPS practice assembled from Augenbrue (2019) and de Wilde (2018), a novel framework should be centred on performance-based functional requirements and system aspects, accounting for the full scope of a building’s functions and interconnected systems, in its social and physical context.

This conceptual framework further incorporates tracking of the propagation of uncertainty (connected to decision confidence), verification methods that account for a universal baseline, and a component-based modelling engine based on the overarching systematic decomposition (providing a modular, scalable, interpretable and generalizable technical foundation).

**Baseline Frame of Reference**

There is a need for a reliable, consistent baseline definition in BPS that aligns with the components of the over-arching conceptual framework. Figure 1 shows a high-level breakdown of aggregate energy components at different reference points in building system operation and/or simulation (corresponding to zone demands, HVAC and plant loads). For example, the sum of individual zone demands (similar to “ideal air loads”), including measures of load sharing and economizer potential. These form the baseline frame of reference; collections of aggregate demands that are in turn transformed by efficiencies and losses due to methods of aggregation, control strategies and system configurations can be compared (i.e. system and plant “transformations”). This separates the (linear) “transformation functions” from absolute estimation methods. Future work could extend the same structure to identify generic geometry template demands (subject to geometry transformations), and climate-agnostic template demands (subject to weather transformations).
**Feature Engineering**

The value of feature engineering is often overlooked even in studies employing supervised black box learning techniques (Fan et al., 2019). BPS suffers from the “curse of dimensionality”, and alignment between bottom-up feature engineering techniques and top-down classification can help reduce the scale of the problem space and reframe parameters in meaningful ways.

Best practice sensitivity analysis can be used to refine the set of important parameters (Reddy et al., 2007), and feature extraction is supported by techniques that decompose and re-constitute a more relevant set of parameters, such as Principal component Analyses (PCA), time series decomposition, or use of autoencoders.

**Time Series Profile Characterization**

Building energy simulations aim to capture the dynamics and behaviour of interacting systems and states over time. Model inputs and outputs therefore take the form of time series representations, including the weather and environmental conditions, functional and occupant behaviour, and operational schedules.

The simplest (and most common) approach in early stage energy analysis is to work with aggregate sum values for relevant loads and demands. However, accurate simulation of the aggregate energy performance of systems requires understanding of time-series profile characteristics – both independently and in relationship to other time series (load diversity) – using abstraction and aggregation techniques (such as moving-average time series decomposition, binning methods, Frequency Response Analysis, etc.).

**Uncertainty**

The characterization and breakdown of uncertainty as it contributes to error is more rigorously analysed in research specific to calibration of energy models to actual metered data (Fabrizio & Monetti, 2015). Typically, this involves either high-fidelity, highly granular, tightly constrained models examining a small subset of controllable parameters or black box statistical methods fit to historic data at a whole-building level. Both cases involve context, tools or methods that have limited application in design stage modelling; however, the development of more advanced surrogate modelling methods that benefit from a blend of high-fidelity simulation and statistical learning methods – coupled with ever-increasing computational power – presents opportunities to leverage lessons-learned from these areas to broader parametric analysis.

Uncertainty can be quantified using Monte Carlo sampling methods; drawing parameter inputs from a priori probability distributions and assessing how this uncertainty propagates through component transformations and outputs.

**Characterizing HVAC Systems**

Augenbroe (2013) emphasizes the unique complications and expertise required to properly model HVAC systems and questions whether a decoupled simulation approach might offer greater diagnostic capability.

Detailed BIM schema used for design, construction and operations describe overlapping building elements and systems with the classes and objects in high-fidelity simulation software, which in turn correspond to high level modelling components. Understanding and defining these translations in an interpretable way is vital for supporting design and operations objectives through all the iterative stages of a building life-cycle.

Characteristics of HVAC systems can be defined relative to objectives explored in early stage design, such as high level ratios between: zonal and central delivery; convective, radiative and conductive modes of heat transfer; hydronic and air-based networks; outdoor and supply airflow capacities.

**Functional Decomposition**

Functional requirements of buildings are often described in a Building Program and assigned to space types; these include thermal comfort, indoor air quality (minimum ventilation, exhaust of pollutants, etc.), light levels and equipment demands.
Production modes interact with environmental sources and sinks to supply thermal energy and mass flow to delivery systems. These involve transformations based on equipment performance and loading conditions. Delivery modes connect one or more modes of production to one or more zone thermal demands. Each delivery mode represents a delivery path through a system with similar stages of thermal and mass exchange sections and common control strategies. HVAC systems can employ a variety of heat transfer media (air, water, glycol, refrigerant, etc.) through delivery networks. The specific configurations, controls and secondary equipment will determine the system response — the efficiency and losses associated with the delivery transformation.

This decomposition allows the problem to be reframed as a series of aggregation and transformation functions applied to energy and mass demand components, based on a breakdown of modes of production and delivery (Figure 1). Determining each component transformation function becomes a sub-problem that can be addressed with a surrogate model trained with a subset of relevant input parameters and aspect outputs (Figure 2).

A component surrogate HVAC modelling approach structured to align with the broader conceptual framework described as part of this research (i.e. with diagnostic techniques from practice as well as statistical calibration procedures from research) would allow high level interaction with the problem space, as well as granular interpretability of performance results and uncertainty.

**Illustrative Example**

An illustrative case study was prepared to demonstrate implementation of the proposed component-based surrogate modelling conceptual framework described above and shown in Figure 2, focusing on the transformation of zone heating demands to whole building Thermal Energy Demands (TED) by a delivery system.

A parameterized, high fidelity medium office building model was constructed in EnergyPlus to generate diverse heating load profiles. Situated in Victoria, Canada, each of the three floors has a floor area of 1,660 m² with perimeter and core zoning, as well as one small IT room. Served by a single VAV system with zonal reheat and perimeter baseboards, the baseline assumptions were assembled based on National Energy Code for Buildings (2015), with adjustment to window performance to amplify demand diversity (USI 4.0 W/m²K, SHGC 0.6).

The sample parameters and ranges are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>units</th>
<th>range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Building Orientation</td>
<td>deg</td>
<td>(-45)–45</td>
</tr>
<tr>
<td>2-5 Window to Wall Ratio (per face)</td>
<td>%</td>
<td>10–90</td>
</tr>
<tr>
<td>6-9 Horiz. Shading Depth (per face)</td>
<td>m</td>
<td>0–1</td>
</tr>
<tr>
<td>10-11 System Heating Sizing Factor (perimeter/central)</td>
<td>0.3–1.3</td>
<td></td>
</tr>
<tr>
<td>12-13 Zone Heating Sizing Factor (perimeter/central)</td>
<td>calc’d</td>
<td></td>
</tr>
<tr>
<td>12 Min Damper Position</td>
<td>%</td>
<td>0–100</td>
</tr>
<tr>
<td>13 Max Reheat Damper Position</td>
<td>%</td>
<td>min–100</td>
</tr>
<tr>
<td>14 Supply Air Low Temp Reset</td>
<td>°C</td>
<td>10–13</td>
</tr>
<tr>
<td>15 Supply Air High Temp Reset</td>
<td>°C</td>
<td>min–21</td>
</tr>
</tbody>
</table>
Using the BESOS platform (Westermann & Evins, 2019) an ANN was created for each scenario (selected for its ability to handle non-linear, discontinuous problem spaces) with 2 hidden layers each with 16 nodes per input, activated with leaky ReLU functions. An L2 regularizer was used to help prevent overfitting on normalized data, along with basic grid search hyperparameter tuning. EnergyPlus inputs were generated using Latin Hypercube Sampling, with variations of the parameters noted in Table 1 (80%/20% training/testing split). Further optimization could offer significant improvement but is outside the scope of this study. The primary objective of the models is to estimate the Thermal Energy Demand Intensity ($H_{TEDI}$, kWh/m$^2$) or the System Transformation ($T_{sys}$). The ANN are trained to minimize Mean Squared Error (MSE), and accuracy is measured with comparison to corresponding high-fidelity simulation results using the coefficient of determination ($R^2$ score). A summary of relevant metrics:

- **Aggregate Zone Heating Demand ($H_{zn}$; kWh/m$^2$):** the sum of zone-level heating demands, independent of the systems serving them, including heat balance results (conductive exchange, infiltration, radiant gains, internal gains, etc.) and additional heat required for minimum required direct ventilation
- **System Heating Transformation ($T_{sys}$):** a metric for the cumulative passive gains, heat recovery, thermal losses and inefficiencies of the delivery systems in a building, measured as a ratio between the Aggregate Heating Demand and TEDI
- **Thermal Energy Demand Intensity – Heating ($H_{TEDI}=H_{T}/T_{sys}$; kWh/m$^2$):** the total heating demand on the production systems, accounting for the System Heating Transformation impacts

Load Diversity metrics help characterize the variation of loads among zones in a building both spatially and over time. The selection used for this study include:

- **Reduction in Peak Demand:** the ratio between the sum of peak zonal heating demands and the peak of the Aggregate Zone Heating Demand profile
- **Reduction in Zero Hours:** the ratio between the decrease in hours with zero heating demand from the average across independent zones and the Aggregate Zone Heating Demand profile
- **Coincident Load Fraction:** the total simultaneous heating and cooling across zones over the course of the year, compared to total zone demand
- **Demand-weighted Quantiles:** proportion of Aggregate Zone Heating Demand from 4 equal part load ranges

**Baseline High Fidelity Models**

The baseline sampling involved 400 annual parametric runs using the EnergyPlus model (approximately 10-15 minutes per simulation). The results are shown in Table 2. Variation in the overall performance of the delivery system is partly tied to the ability for the VAV system to centrally manage diverse loads with constrained setpoints, damper positions, and minimum ventilation requirements. Potential confounding factors that were not fully investigated as part of this study include unmet heating demands and inherent underventilation; however, fewer than 34 samples had unmet hours more than 1% of a year.

### Table 2: Summary of outputs from 400 high fidelity simulation runs of example office building

<table>
<thead>
<tr>
<th>Metric</th>
<th>Min</th>
<th>5%</th>
<th>25%</th>
<th>Mean</th>
<th>75%</th>
<th>95%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_{zn}$ (kWh/m$^2$)</td>
<td>30.5</td>
<td>38.7</td>
<td>50.3</td>
<td>69.3</td>
<td>81</td>
<td>118.2</td>
<td>243.6</td>
</tr>
<tr>
<td>$T_{sys}$</td>
<td>0.48</td>
<td>0.58</td>
<td>0.76</td>
<td>0.85</td>
<td>0.95</td>
<td>1.04</td>
<td>1.18</td>
</tr>
<tr>
<td>$H_{TEDI}$ (kWh/m$^2$)</td>
<td>31.7</td>
<td>38.9</td>
<td>56</td>
<td>87.1</td>
<td>107.4</td>
<td>178.1</td>
<td>347.1</td>
</tr>
<tr>
<td>UHH</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>40</td>
<td>10</td>
<td>181</td>
<td>2940</td>
</tr>
</tbody>
</table>

**Preliminary Surrogate Model**

The first surrogate ANN was trained using the full set of parametric sample inputs, with the objective to directly estimate the final TEDI output. Figure 3 shows the model results for both the training and testing set, with an $R^2$ scores of 0.96 and 0.94 respectively.

**Component-based Surrogate Models**

The next set of component-based surrogate models was trained to estimate the System Transformation based on the conceptual framework of Figure 2. Three versions of this approach were generated using: a) the original full parameter set; b) the subset of system parameters only; c) Load Diversity metrics and system parameters. The accuracy of each surrogate model is listed in Table 3, with the final surrogate results plotted in Figure 3.

**Table 3: Surrogate model accuracy**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$R^2$ - train</th>
<th>$R^2$ - test</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) Full Parameter Set</td>
<td>0.87</td>
<td>0.83</td>
</tr>
<tr>
<td>b) System Parameters only</td>
<td>0.79</td>
<td>0.74</td>
</tr>
<tr>
<td>c) System &amp; Load Diversity</td>
<td>0.89</td>
<td>0.88</td>
</tr>
</tbody>
</table>

**Figure 3: Comparison of output from preliminary surrogate model and final component surrogate model to baseline results**

**Uncertainty Application**

As an extension to this illustrative example, a problem was considered where the objective is to understand the range of potential TEDI values in the face of uncertain loading conditions, for a building designed to meet Passive House heating performance (15 kWh/m$^2$). In this case, the overall annual tenant office demands can be estimated with significant confidence, but characteristics of load diversity are much less certain.
For this simplified scenario, demand and load diversity parameters were assumed to be represented using Gaussian normal probability distributions. A Priori mean and standard deviation were roughly approximated using expected values and ranges; specifically, range bounds were estimated (95% typical conditions) and translated to initial standard deviation values:

- Aggregate Zone Heating Demand \( (H_{in}) \): +/-2% of target expected demand
- zero load hours: +/- 400 hours (annually)
- coincident loading: 5-25% of total heating
- peak heating load: +/-10% variation from design
- part load profile: variations of +/- 20% base heating loads (1st Quartile loads balanced across other part load ranges)

The final uncertainty profile of the TEDI output was generated through Monte Carlo sampling of the uncertain inputs, which were run through the Component-based Surrogate Model (10,000 runs). The surrogate model allows rapid processing of the samples (total computation time: 28 ms); attempting to conduct this study using the EnergyPlus model directly would take approximately 2083 hours, making it an infeasible option in practice. The final output results are shown in Table 4.

**Table 4: Summary of results from 10,000 runs of component surrogate model under uncertain load conditions.**

<table>
<thead>
<tr>
<th>( H_{in} ) (kWh/m(^2))</th>
<th>( T_{sys} )</th>
<th>( H_{TEDI} ) (kWh/m(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>11.4</td>
<td>0.65</td>
</tr>
<tr>
<td>5%</td>
<td>11.9</td>
<td>0.74</td>
</tr>
<tr>
<td>25%</td>
<td>12.1</td>
<td>0.79</td>
</tr>
<tr>
<td>mean</td>
<td>12.3</td>
<td>0.82</td>
</tr>
<tr>
<td>75%</td>
<td>12.4</td>
<td>0.86</td>
</tr>
<tr>
<td>95%</td>
<td>12.7</td>
<td>0.90</td>
</tr>
<tr>
<td>max</td>
<td>13.2</td>
<td>0.96</td>
</tr>
</tbody>
</table>

This illustrative example demonstrates how uncertain load diversity conditions could amplify uncertainty in actual operational TEDI for a given HVAC system configuration, potentially impacting decision-making regarding energy offset capacity for net zero design and operation and/or highlighting a need to refine mechanical system design and control strategies.

It is also important to account for the model uncertainty inherent in the use of the surrogate. One approach would be to incorporate it as a compounding mean standard deviation applied to the estimated output (+/-5.7% for this illustrative case study surrogate model).

**Conclusions**

With the final component surrogate model, sources of uncertainty can be traced through intermediate characterization parameters and component transformations, both of which are more easily interpretable (and estimable) and better isolate the types and sources of uncertainty (and amplification/attenuation of uncertainty). Neither the monolithic surrogate model nor the high fidelity simulation allow this direct interpretability. The latter could also require infeasibly long computational time for larger uncertainty analysis problems, though it would eliminate the model uncertainty inherent in the surrogate approach.

By breaking out the system transformation from overall load estimation (as an intermediate output for diagnostic purposes), exploration of the influence of design parameters on system response becomes more transparent.

Extending the approach to the broader set of components would allow modular configurations and scalable fidelity: components of interest could be swapped for bespoke surrogates trained over an advanced simulation engine, while order-of-magnitude estimates can be included for component transformations of lower importance.

**Future Work**

The preliminary component-based surrogate modelling framework outlined in this paper is intended to address the lack of HVAC modelling in early stages of design development, and to find connections to high fidelity BPS practice and research. The following major areas have been described, but require significant further investigation:

- Triangulation with qualitative, top-down study of stakeholder needs, helping define types of problems and sets of performance-based requirements and supporting intuitive design space exploration
- Rigorous bottom-up sensitivity analysis to support feature engineering and model order reduction, (Principal Component Analysis, Autoencoders, etc.)
- Improvement of the foundational surrogate modelling methodology, to improve accuracy and generalizability
- Refining protocol for consistent estimation of frame of reference load components
- Apply Systems Approach for formalizing functional decomposition aligned with detailed schema
- Extension to templatized geometry and climate components, advanced co-simulation (using equations-based engines) or related domains (e.g. natural ventilation, daylight simulation, etc.)
- Uncertainty - breaking out sources of uncertainty and tracing them through to outputs – allowing defaults, generic estimates, or detailed uncertainty scenarios
- Exploring options for integrating uncertainty methodology into framework (such as Bayesian Calibration), whether using sampling protocols, embedded uncertainty metrics, or innovative metamodel structures (e.g. Gaussian Processes)
- Characterizing time series profiles for aggregate analysis (Frequency Domain Analysis, etc.)
- Characterizing HVAC system architecture using high level, interpretable parameters relevant to early stage design (Controls Theory, Graphs, etc.)
- Characterizing zoning boundaries and assignment heuristics
- Rigorous validation of the methodology through design of experiments grounded in comprehensive EnergyPlus simulation test cases
References


