# A Bayesian model for emulating building model performance and uncertainty analysis

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**How many CV(RMSE) and MBE are in each energy subcat that qualify as calibrated model.**

# **Abstract**

A validated building model containing detailed thermophysical properties of the case study building and local weather data is used together with expert judgement of uncertainty bands on the parameter input to train a Bayesian emulator. Parameter input was assumed with a Gaussian distribution and posterior distribution of energy and environmental data was examined against actual measurements at monthly and hourly intervals.

Actually one of the findings of this work could be that although the model produces initial results that are very close to the measured values, when looked at from a broken down perspective, they differ widely from available benchmarks and area-weighted field measurements. This highlights the need to have a set of guidelines describing in more realistic terms the need for accurate parameter inputs of models.

Also quit often analysts do not have high resolution data of buildings, if we can demonstrate how much uncertainty is involved in the model if it is to be calibrated based on the monthly available data then it is of great use to the simulation community.

The purpose of this work is to use actual monthly energy and environmental data, and reported uncertainty ranges of building fabric and plant efficiencies, as well as typical consumption data to train a Bayesian emulator to reduce the space of parameter input uncertainty.

Having put the deterministic occupancy and operation of the building as closely as possible, and having used local weather data, the probable variation in fabric properties and plant efficiencies could only bring 7 out of 12 months into a calibration band of +\_15% (CV(RMSE)), with the rest of uncertainties having to be left to micro-climate, weather, stochastic occupant behaviour and

We argue that the inclusion of zone environmental conditions (i.e. air temperature) is crucial to the quantification of building energy model uncertainty.

# **Introduction**

Stating uncertainty bands and integrating them in building performance simulation results is essential for producing high-quality results that also adequately acknowledges modelling limitations. Both modelling uncertainty and performance gap between model predictions and actual building operational data are areas of active research, and sadly a recent article found that a large proportion of building modelling community lacks essential knowledge on what the most fundamental parameter inputs for buildings are and how these impact the model predictions [1]. This gap has major consequences as retrofit strategies are mostly derived in consultation with energy modelling and as such techno-economic benefits of proposed solutions can be exaggerated and misjudged. Similarly future buildings are expected to be more responsive to other civic activities (i.e. power generation and storage, transport, etc.)[2]. This can only be assessed by modelling, simulation and near-real-time analytics of a cluster of buildings at district and potentially city level which in turn requires generating accurate building energy data without the time-consuming limits of existing first-principle-based physical models.

This work introduce a Bayesian method of uncertainty quantification applied to building modelling uncertainties. A detached property where detailed information on occupant activity, fabric properties, plant operations and appliances energy consumption was available was instrumented to collect electricity, gas and space temperature data in order to examine and introduce a modelling framework aimed at developing guidance to intermediate level building modellers for producing simulation results within acceptable uncertainty boundaries. Building model parameter space and predictions suffer both inaccuracy and uncertainty due to:

1. The dynamic nature of building fabric thermo-physical properties (i.e. The U-value of a masonry wall changes as a function of its moisture content, while most models assign a fixed value to this), with hygroscopic material exhibiting wide thermophysical variance at different moisture and temperature conditions.
2. The stochastic nature of occupant behaviour and his/her interaction with the building (window opening, light and power usage).
3. Uncertainties and variations in plant operational characteristics.
4. Exact zone air exchange figures and fabric infiltration values which are difficult to determine, with the later only available after a building pressure test that is logistically difficult and costly particularly for larger occupied buildings.
5. The weather files that impose large uncertainties in particular with solar irradiance data that quite often is partially or fully modelled (as opposed to measured), and micro-climatic variations that are widely ignored and understudied. An example could be the difference in conventional airport weather station data used to model urban settings. Airports are by definition exposed terrains often with close proximity to water to facilitate emergency aircraft landing. Annual weather files compiled in these locations would therefore report higher wind velocities and miss the heat-island boost of temperatures that is increasingly separating urban and open country micro-climates.

The aim of this paper is to outline a Bayesian method of uncertainty analysis using the aforementioned property and local weather file data. In doing so we attempt to first outline the sources of uncertainty and how they can propagate within the model. Actual monthly energy data (natural gas and electricity) are used to enable initial history matching and subsequent forward uncertainty analysis, while hourly indoors temperature from 2 locations are used to undertake inverse uncertainty analysis.

This work also seeks to examine if such a detailed energy model can be successfully replicated by an emulator so that such a model or a combination of them could present the behaviour of a demand side energy system for wider system level of energy modelling.

One of the conclusions can be that these models were not designed to take into account the interaction and behaviour of the occupant with the building. Although the authors were completely aware of the details of how the building was used over the past year, the lack of this knowledge could have been predicted in this instance by an experienced analyst.

# **Literature review**

A wide range of reasons exist that lead to building energy analysist using assumptions in place of hard to measure building and occupant parameter inputs. These have a major impact on the prediction accuracy of the model. An analysis of two office buildings in Australia found cooling set-points, ICT and its schedule and lighting power density to impact the predictions of energy models most, leading to for instance lighting retrofit paybacks that can range from 2.4 to 10.3 years[3].

Fabric properties

An area of large uncertainty is the fabric thermophysical properties. While the composition, properties and dimension of all fabric elements for the case-study building is known, uncertainty, simplification and error arise due to non-homogeneity of material, geometrical discontinuity and variation in U-Value as a function of material moisture content. Most notably the hypothesis of mono-dimensionality of heat flow which is fundamental to ISO 6946:2007, ISO 9869-1:2014, CIBSE and ASHREA [4-7] material thermal resistance (or U-Value) calculation is not entirely valid. Heat moves in a diffused and 3 dimensional manner which building energy models are incapable of replicating. Existing techniques for in situ measurement of fabric U-Value show notable variations [8-11], and while the main standardised semi-stationary and dynamic U-Value measurement calculation methods produce results that mostly reveal reasonable differences [9], in some cases departures of up to 393% are reported between measured and calculated figures [8]. Traditional masonry elements [12, 13] as well as floors [14] have been found to perform better than calculation method suggested with composite walls reported to perform worse than model calculations. On average, A. Marshall et al. found CIBSE model over-predictions of U-Values for brick walls, ceilings and doors to be 30.3%, 15.5% and 9.9% respectively while calculated window properties showed much better matches with measured figures [15]. A study of 57 properties found that while variations between similar wall types and even within the same dwelling’s walls existed, 44% of walls performed better than CIBSE predications, 42% were within acceptable bounds and only 14% of sampled walls performed worse than calculations suggest [16], however measured and calculated floor U-values were found to be in good agreement. Difficulties in indentation of the composite material and their density and moisture content, internal and external air velocities, fabric non-homogeneity and cumbersome nature of in-situ fabric studies are notable reasons behind fabric U-value errors and uncertainty. Nonetheless within a data-reach simulation environment and with careful parameter input selection, building energy models have been shown to predict energy and environmental performance of a building with high levels of accuracy [17]. Given that even a 5% increases in fabric U-value was reported to raise energy consumption of family homes by 0.3-2.5% [18], a uniformly distributed uncertainty band is imposed on elemental U-Values to reflect similar magnitude of variations reported in literature, as outlined in table 2.

In the absence of a rather convoluted air permeability test, actual building infiltration rates are similarly difficult to arrive at. Table 4.16 of CIBSE guide A [5] outlines a range of 0.25 to 0.95 ACH for various 2-storey buildings below 500m2 with a value of 0.5 ACH describing typical constructions similar to this work’s case-study building. Therefore 0.5 ach informed the validated base model with 0.25-0.95 ACH representing the range of possibilities that batch-sims in the Bayesian emulator explored (see table 2).

W. Tian et al. notes the need for further research to provide clear guidance on the number of sampling numbers required for building energy analysis [19].

# **Case-study building**

A detached two storey masonry construction built in 1994 was selected as the case-study building. Two occupants are the sole users of the dwelling and given a very predictable pattern of occupancy (both occupants have 8am-5pm working commitments), it was possible to limit the stochastic nature of occupant behaviour as far as practically manageable, and more closely represent the occupancy by the deterministic schedule imposed on the model. The building (with a gross area of 168.66m2 and 19.73m2 of unheated space) is located in a built-up urban surrounding, is only partly shaded (on its west-elevation) by another adjacent property (which was taken into account within the modelling work). In 2016 the property had an observed annual gas (15,381 kWh) and electricity (2,991 kWh) consumptions that fall within respectively high and medium UK typical domestic consumption values [20]. UK average domestic hot water usage are reported as 142 l/person/day [21] and 122 l/person/day [22], and the occupants assessment was that their specific consumption is well below this figure (given that they were heavy users of gym washing facilities) and expected to use no more than 50 l/person/day.

# **Data collection**

Marketplace offers a wide range of environmental and energy sensors and as such a proprietary set of sensors were deployed for this project (Fig ??). To reduce measurement uncertainty, each one of the two target zones were equipped with two separate air temperature sensors located at different locations of the same zone at 1.3m above floor level and logging at 30s intervals to achieve a moderated average. Similarly the electricity was logged using two clip-on current sensor CT on the incoming live cable at 10s intervals and the two set of similar readings were averaged and aggregated to form the measured values.



Figure 1 LSH: power monitor, RHS: AC current sensor, monitoring transmitters and temperature sensors.

In order to parameterise the energy model more accurately, a plugin power monitor was used to characterise instantaneous and time-averaged consumption of the mail electrical devices in the property. Gas consumption was however logged manually at monthly intervals using the main gas meter.

<https://wiki.openenergymonitor.org/index.php/EmonTH>

# **Method**

Using manufacturer’s and the house-builder’s literature, a detailed set of parameter inputs are compiled and where the greatest quantifiable uncertainty existed, lower and upper bands are imposed on the input value used. These bands were so far as possible derived from scientific literature and used to dictate the size of associated variations explored in batch-runs (Table ??).

Floors are less prone to variations in internal and external air velocities that act on walls and roofs more robustly, and lead into dynamic heat transfer values that fail to be captured by standardised calculation methods. Therefore a smaller uncertainty margin was derived from literature and imposed on floor thermal resistance figure.

Gas consumption data was available at monthly bases, and electricity was logged at 5s intervals. Space temperature was recorded by two sets of double sensors positioned in the south facing master and north facing kitchen areas. Electricity and gas data required no imputation but losses of 5.7% and 2.7% of the total annual data from Kitchen and master bedroom spaces required imputation, where each missing hourly temperature cell was imputed by the average of the previous and successive available cells.

The property’s glazing was updated in 2009 and manufacture’s literature state the G and U-value of the fenestration to 0.691 and 1.788 W/m2K respectively, with respective error bands of ±5% and ±2%. The compound upper and lower limit of these two values altered the gas consumption of the calibrated model by ±2.05 kWh (± 0.013%). Given its negligible nature, the error bands of the glazing were discounted. The compound effect of all other uncertainty bands created a lower boundary of 8,842 kWh and an upper boundary of 26,452 kWh with respect to an observed gas consumption of 15,381 kWh (i.e. -42.5% to +72%).

Through a succession of 38 models each with incremental adjustments paved the way to arrive at the final version containing local 2012 weather files. Against actual hourly data, ASHRAE Guideline 14-2002 was followed to calibrate the building model [23]. This entails determining two dimensionless indicators of errors, MBE and CV(RMSE) values using formulae 1 and 2:

[1]

[2]

Where *Mi* and *Si* are respective measured and simulated data at instance *i*, and *Ni* is the count of the number of values used in the calculation. ASHRAE Guide 14 considers a building model calibrated if hourly MBE values fall within ±10% and hourly CV(RMSE) values fall below 30%. MBE and CV(RMSE) indices were constructed over monthly intervals in order to study monthly variations too. MBE figures provide an indication of errors averaged to the mean of measured values but suffer from the cancellation effect. CV(RMSE) index however is a measure of accumulated error normalised to the mean of the measured values. As such CV(RMSE) more closely reflects the accumulated magnitude of error and therefore is a better measure of the overall prediction accuracy of the model.

1. A base model is developed and validated to have MBE and CV(RMSE) values within ASHRAE acceptance criteria.
2. 7

It is worth noting that EnergyPlus calculates infiltration for each zone dynamically using an Air Flow Network component that returns dynamic values at each time step as a function of a crack factor value (a user-defined input) and air pressure differentials across all boundary surfaces with air to both sides [24], with HVAC-induced infiltration also accounted for where mechanical air systems are modelled. In order to vary the input value for infiltration across batch simulation, dynamic infiltration airflow rates were used to create an infiltration intensity schedule (ranging from 0 to 1) for every zone. This schedule was then used with an overall peak value ranging from 0.25 to 0.95 to allow the infiltration to be dictated at each run, with individual zones having a value equal to their infiltration intensity multiplied a peak ach in 0.25-0.95 range.

The schedule (i.e. timetable) that governs the timing of heating in the building impacts the timing of the gas use greatly as it dictates when heat is requested in the occupied zone. Heating schedule presents a multitude of choices that are a product of any variation of 12 months X 7 days X 48 half hours presenting a large number of possibilities. Since the injection of heating into the space should coincide with a rise in space temperature, the actual recorded data in two target areas were used to arrive at the closest match between the recorded and simulated space temperatures [report how close the data has been]…

Gas consumption

|  |  |  |  |
| --- | --- | --- | --- |
|  | Total Measured | Total simulated |  |
|  |  |  |  |
|  |  |  |  |

In UK, cooking as a proportion of total household energy demand has halved since 1970s, however over the last 10 years of the latest UK household energy survey (2001 to 2011), it has remained notably constant and equates to an average of 2.67% [-0.37% to +0.23%] of overall household primary energy demand [25].

**4.1 EnergyPlus load and temperature predictions**

EnergyPlus is a collection of dynamic modules each simulating different environmental, climatic and operational conditions that define either the flow or the stored quantity of energy within building internal zones. Principally however the core of the programme is a heat balance equation that is solved using one of three methods (3rd order backward difference, Euler method or analytically) in order to converge zone loads and resultant temperatures to within a pre-defined tolerance range, using a predictor/corrector process. Energyplus’s uniqueness lies in being a physically-based modelling solution that oversees a simultaneous calculation of radiative and convective heat and mass transfer processes, adsorption and desorption of moisture in building elements, iterative HVAC plant and building fabric and air interactions and accurate temperature and comfort predictions. This integrated and simultaneous simulation process is completed via several modules (and overseen by EnergyPlus simulation manager), with understandably multiple first-principle-based equations are solved simultaneously and/or iteratively, which makes it very difficult to bring a sharp focus on any single or sets of expressions where model prediction uncertainties lie. However interestingly the zone air heat balance equation is the primary mechanism that connects the loads within a zone, the corresponding plant duty to offset the loads and maintain target temperatures and finally the zone mean air temperatures (see Expression 3).

[3]

Where:

is the accumulated thermal energy in the zone air

is the sum of convective internal loads

is convective heat transfer from the zone surfaces

is the change of the room air enthalpy as a result of zone air mixing

is the HVAC system input to achieve its target temperature

Given that E+ assumes a uniform zone air and surface temperatures, uniform long and short wave radiation and diffuse radiation and reflective surfaces (as opposed to direct or point-based), it is reasonable to regard zone air temperature as the interconnection where connective, radiative and convective heat balance and mass transfer are realised.

Essentially each item on the right hand side of the equation indicates a change of enthalpy due to environmental perturbations.

# **Results and discussion**

If a larger number of trials existed where the results of measured vs. calculated fabric U-Values were reported in relative terms, it would be possible for energy modelling communities to impose fabric error bands with a greater degree of uncertainty.

Despite a high fidelity model that was populated by actual data that are of high integrity, the prediction of gas consumption remains less accurate than electricity. The roll out of smart gas meters in the UK are therefore a critical development if a more refined perspective of energy flow in the built-environment is to be accomplished.

* Disparity reasons:

Authors of this paper reported on a previous model calibration where EnergyPlus temperature prediction was reported for a larger structure with openable windows to the north aspect of the building only. A smaller domestic property has a much smaller thermal mass within its insulated fabric and therefore large openable windows (as well as doors) provide the opportunity for very rapid purges of internal air that leads to space air temperature dropping dramatically. While within a large building with considerable mass, the core temperature of the mass acts as a moderating anchor and window opening events do not create major temperature swings, a smaller property remains more susceptible to notable swings following window opening events.

Overall the actual room air temperature results show that in the absence of heating system input (i.e. in the freefloat mode), the building cools down more slowly than the model suggestion. This could be due to the absence of exact thermal mass contributed by furniture and furbishing that stores heat and also slows down the internal convection currents that are a major cooling mechanism within the space. Secondly mature trees and shrubs around the house provide a greater degree of sheltering that cannot be represented within the model.

* Insufficient data is available to support assessment and variation of measured versus calculated fabric U-Values and in particular with external walls that are more instrumental in energy performance of a property, a wider range of field trials could inform better parameterisation of energy models.
* Floor and roof thermal values impose smaller uncertainty bands due to the thermally coupled nature of non-suspended floors with the ground, and in roofs due to the buffeting effect of the lost space. If closer values for actual thermal values were sought, an in-situ measurement of wall U-values could be taken as the first priority.

# **Conclusions**

What is the electricity and gas profile of 21 Prince’s meadow if all the schedules and activity descriptions were set to default or industry normal practices?

When using measured data to inform a Bayesian uncertainty quantification, the posterior distribution derived using Bayesian technique

Available observed data for building thermal and DHW load were aggregated at whole building level and at monthly intervals, leading to insufficient insight to infer subcategories of loads with greater confidence.

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Table 1 Parameter inputs for energy model development of the case-study building

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Description** | Uncertainty range |
| Heating | Natural gas boiler serving a radiator central heating system |  |
| Heating setpoint (setback) | Master Bedroom: 19°C (16°C) - Kitchen: 19°C (16°C) | 17.5°C-20.5°C |
| Heating schedule | 02:00-11:00 + 16:00-24:00 |  |
| Ventilation | Natural ventilation (mechanical extract to family bathroom and en-suite) |  |
| Ventilation rate | Highly stochastic, controlled by occupants via openable windows |  |
| Gas boiler seasonal efficiency | 65% (15 years old non-condensing gas-fired system boiler – 77°C/55°C F+R) | 60% - 75% |
| DHW consumption | 0.3 litre/m2/day |  |
| Cooling setpoint (setback) | Uncontrolled |  |
| Nominal lighting power density | 1.4 W/m2  (manually controlled) to achieve 200 lux |  |
| Occupants | 2 people in total |  |
| Internal gains[a] | 6 W/m2 |  |
| Gross (conditioned) area | 168.66m2 (148.93m2) |  |
| Observed annual gas (electricity) consumption (2016) | 15381 kWh (2991 kWh) |  |
| **Fabric properties:** |  |  |
| Glazing (with low emissivity coating) | 1.788 W/m2K (3mm self-cleaning pane, 20mm Argon filled cavity, 3mm low emissivity pane) | |
| Glazing G Value (solar transmittance) | 0.691 |  |
| External walls [b] ( W/m2K) | 0.544 | ± 15% |
| Roof [c] (W/m2K) | 0.213 | ± 15% |
| Floor [d] ( W/m2K) | 0.335 | ± 5% |
| Infiltration (ac/h) [e] | 0.5 | 0.25 - 0.95 |
| [a] Electricity (ICT and appliances): 3 W/m2; Gas (Catering): 3.3 W/m2 | | |
| [b] 100mm brickwork, 50mm Stonewool insulation, 100mm blockwork, 10mm plasterboards | | |
| [c] 25mm Clay tile roofing, loft space, 180mm glass fibre quilt insulation, 10mm plasterboards | | |
| [d] 100mm cast concrete, 7mm screed, 4mm high gauge polythene DPM, 5 mm foil-backed underlay , 15mm solid wood flooring | | |
| [e] Empirical values derived from table 4.16 (CIBSE Guide A) for a two storey property on normally exposed site | | |

Table 2 Input parameter variations for Bayesian emulator development

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 |
| Description | Heating  setpoint [17.5°C-20.5°C ] | Boiler seasonal efficiency | External wall U-value | Roof U-Value | Floor U-value | Infiltration rate (ach) | DHW consumption  (L/day/person) | Cooking |
| Base model input (1st wave) | 19°C | 65% | 0.544 | 0.213 | 0.337 | 0.5 | 300 (1st wave)  120 (2nd wave) | 3% of total domestic energy use |
| Base model input (2nd wave) | 17.5°C | 65% | 0.544 | 0.213 | 0.337 | 0.5 | 120 |  |
| Range of variation | ± 1.5°C | 60% – 75% | ± 15% | ± 15% | ± 5% | 0.25 to 0.95 | 70-250 L/day | 1.05% - 6.3% |
| Rational | [a] | [b] | [c] | [c] | [d] | [e] | [f] | [g] |
| Uncertainty quantification | Forward | Forward | Forward | Forward | Forward | Forward | Inverse | Inverse |
| Element varied in E+ batch simulations | Heating  setpoint | Boiler seasonal efficiency | Wall cavity Insulation thickness [ 40mm-63mm] | Insulation thickness [150mm -210mm] | Insulation thickness [45mm- 55mm] | [e] |  |  |
| [a] Manufacturer’s room thermostat resolution reported at ± 0.5°C with an additional ± 1°C allowed for time-dependent drift degradation.  [b] Boiler insulation, heat exchanger and working fluid degradation, limescale and total dissolved solids leading to an accumulated min and Max performance degradation of 4% to 23% [26, 27]. These levels of degradation were imposed on boiler manufacturer’s quoted efficiency of 78%  [c] Although most literature report in-situ wall and roof measurements to be better than elemental method calculation suggestions [13, 15, 16], an equally distributed ± 15% imposed to first cater for all eventualities, and also enable the uncertainty emulator to assess the entire Latin hypercube space (including worst scenario range).  [d] as per [c] although the magnitude of variations reported for floors were smaller than those of walls/roofs [16] and non-suspended ground floors with no air cavities have much greater thermal unity [28] so a tighter band of ± 5% was imposed to reflect literature findings.  [e] As outlined in the last paragraph of sections 2 and 4.  [f] From field measurements of DHW consumption in the UK [22] where the mean DHW consumption per person in the UK is reported as 122 litres/day ± 18 litres/day (i.e. ±15% variation) leading to mean DHW energy consumption of 16.8 MJ/day ± 2.2 MJ/day (95% statistical confidence). In the 1st wave the model input was a much larger values of >300l/day and 53MJ/day, However the model predictions were calibrated to return close results to the observed energy consumption for the case-study building given its high fossil fuel consumptions.  [g] Cooking has been observed to currently account for an average of 3% of total household energy demand with historical data also indicating a maximum of 6% [25]. This observed data informs the average and maximum cooking demand with 1% also selected by the authors to represent a probable lower boundary. | | | | | | | | |

Questions for Hailiang:

1. A graph of grid co2 projections that are not linear.
2. What does the Baysian emulator tell us when we prescribe fabric U-values that are worse than the base model? Because most literature report that measured fabric U-values are better than standard elemental calculation methods. And if we possibly can make few suggestions for building modellers to use better than prescribed fabric methods? Let’s think about how this work could be of use to practitioners/energy analysts.

V7 and V8 simulation:

1. The 7th variable being DHW parameter input whereby we will vary the DHW peak flow rate (using the WaterUse:Equipment object as your explanation below).
2. The 8th variable will be the cooking gas consumption parameter input that we will vary via the [OtherEquipment](https://bigladdersoftware.com/epx/docs/9-0/input-output-reference/group-internal-gains-people-lights-other.html#otherequipment) object, assigned only to the kitchen area with a power density of 3.3 W/m2 ( as I said despite assigning it in my DSB model I couldn’t find it in the E+ model attached – could you please see if you can?).

Sequence of uncertainty analysis on building energy models

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1. Parameter selection | | | 2- sampling | | 3- simulation | 4- post processing | | 5- Additional functions |
| Categories of uncertainty analysis | Aim | Method | Description | Aim | Method (example) | Variations | Description | Method (tools) |  |
| 1: **Forward**:  Uses input uncertainty variation to assess the impact on model output uncertainty | Selecting all key factors effecting simulation outcome | Sensitivity analysis  Standardised rank regression coefficient (SRRC): | Deciding on the distribution form of parameter and a true representation of the range | To produce low-discrepancy simulation input sequences and enable full coverage of possibilities | Independent Variables:  Quasi-Monte carlo  Sobol, Halton, Faure [125]  Correlated Variables:  Iman/Conover, Dependence-tree copula, Stein [36] | 2D Monte-Carlo  (differentiates the impact of aleatory and epistemic uncertainties)  Incremental sampling  Statistical surrogate models (i.e. data fit/reduced order models) | Examining model response to each input parameter variation (i.e. signal change) | Batch simulations (automated by jEPlus/GURA-W) | HVAC system sizing [31] |
| 2: **Forward**:  None sampling uncertainty propagation | Parameter distribution is represented using:  Perturbation/most probable point-based/generalised polynomial chaos | | | N/A | | Faster in convergence than sampling but not as robustly audited as sampling methods. |  |  |  |
| 4: **Forward**:  None probabilistic | Instead of a probability distribution, parameter inputs are assumed within an interval domain. | | | As per [1] | Interval analysis, fuzzy theory, Dempster-Shafer evidence theory, affine arithmetic model. |  |  |  |  |
| 3: **Inverse**:  Using measured data to assess model input uncertainty | Often main input parameters are selected using a sensitivity analysis. | | | As per [1] | Normal distribution  Stochastic optimisation  Latin Hypercube  Gradient-based [8]  Bootstraping [17] | Frequentist technique: uses measured data to estimate an input parameter  Bayesian method: unique in deploying expert knowledge to quantify uncertainty | | | |

1. A condensed outline of notable categories of uncertainty analysis and their associated method breakdown