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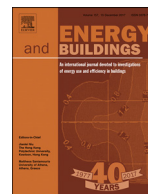
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A comparison of methods for uncertainty and sensitivity analysis applied to the energy performance of new commercial buildings

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ABSTRACT

An Energy Performance Contracting (EPC) is a financing agreement offered by general contractors that enables cost savings from reduced energy consumption to building owners. To create such an offer, the contractor has to provide an energy consumption threshold and a measurement plan.

This article aims to draw some recommendations to choose an appropriate approach to provide the information necessary to create the contract, regarding computation time budget, expected accuracy and type of information provided.

To get these results, we couple thermal simulations to various uncertainty and sensitivity methods.

We first compare screening and differential sensitivity to reduce the number of inputs of the statistical study. Then, we analyze various uncertainty analysis methods to set an appropriate energy consumption threshold, considering the input uncertainties and the study context (Quadratic combination, directional and importance sampling and reliability methods).

Sensitivity analyses in various input spaces are then carried out to identify the most critical contributors to energy levels to create the measurement plan. Finally, two metamodeling approaches are tested to reduce the overall computational time: Kriging and sparse polynomial chaos.

These methods are tested and compared on a 4000 m² office building in Nantes, France. The resulting recommendations can be applied to any building, depending on the model regularity, the number of uncertain parameters and the objective of the study.

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1. Introduction

Since buildings are responsible for around 40% of total energy [1], many initiatives have been developed to build more sustainable buildings. For instance, in the European Union, all new buildings have to be “nearly zero energy” by 31 December 2020 [2]. With this in mind, Energy Performance Contracting (EPC) is becoming a key priority for decision makers.

EPC is an innovative financing arrangement that enables cost savings from reduced energy consumption. Usually offered by general contractors, it allows building users to be ensured of the energetic performance of their building. Indeed, building users are paid by the contractor if the measured energy consumption of the building does not meet the contract requirements. On the contrary, if the building is more efficient than expected, the contractor can earn a financial reward. In some cases, the

contractors offer to repay the cost of installing energy conservation measures. The terms of the contracts are defined at the very beginning of a building project, before the construction starts. Two crucial information has to appear in this type of contracts: an energy consumption threshold and a measurement plan to monitor critical parameter and identify the reason of a possible overconsumption.

Before building construction starts, thermal simulation tools are often used to predict the required energy levels [3]. User behavior and climate play a significant part in the levels needed by the building [4]. Thus, energy consumption should be adjusted based on some variables reflecting the actual occupancy and climate during the guarantee period. Due to lack of certainty with regard to unknown parameter levels at the design stage, or manufacturing defects at construction stage, building and HVAC systems need to be measured by uncertainty analysis. This article focuses on the specific parameters that the contracting companies are responsible for measuring as part of the performance guarantee.

As thermal simulations are carried out during the design phase, a significant amount of input data is still hypothetical and subject to change. Therefore, coupling a simulation with uncertainty

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and sensitivity analyses allows taking into account the inputs uncertainty to get the necessary information for an EPC. Defining a performance guarantee requires two steps:

- State a consumption threshold for the performance guarantee taking into account the uncertainties.
- Identify the critical parameters (quality procedure) during the design phase in order to reduce the risks of non-compliance of the contract.

This study aims to analyze the suitability of various uncertainty and sensitivity analysis methods for building the EPC and propose a method for practical use. Part 1.1 and 1.2 define the concepts of uncertainty and sensitivity analysis and how and why they are currently applied in the building field.

1.1. Sensitivity analysis

Sensitivity analysis methods are applied to study a model response to the variation of input data in order to identify the impact on the output. It provides valuable information on the model, such as understanding what is influencing the levels of the key parameters and their interactions. Sensitivity analysis methods aim to identify the most influential parameters in order to reduce their uncertainty, to simplify the statistical model by eliminating non-influential inputs or grouping correlated inputs. Sensitivity analysis methods can also be used to check whether the physical model correctly describes the phenomenon and to refine the input space by removing absurd realizations.

Saltelli classified different approaches of sensitivity analysis [5]:

- **Local methods:** where one parameter varies at a time, the other being set.
- **Global methods:** quantifying the influence of the parameters on their whole variation range to determine their impact on the output, ordering them by their level of importance.
- **Screening methods:** covering all the input space to determine the most influential inputs qualitatively with a few simulations.

Local and global methods provide a quantitative result determining the weight of each input variable on the outputs, whereas screening methods give qualitative results highlighting parameters with important or negligible effects relative to each other without knowing their global impact.

Local differential sensitivity analysis methods are widely used in building simulation. Macdonald implemented a local sensitivity analysis method (differential sensitivity) in ESP-r [6], a modeling tool for building performance simulation. Westphal and Lamberts [7] applied the influence coefficient suggested by Lam and Hui [8] to select and sort by importance the parameters that should be calibrated during the dynamic thermal simulation. Merheb [9] recommends using local sensitivity analysis to reduce the number of parameters to 20 in order to build a metamodel to study the uncertainty and sensitivity of the building model. Other local methods based on approximation models (FORM/SORM) exist in statistical literature but are not yet applied in building performance case studies.

Unlike local methods, global methods are employed to study the impact of parameters throughout the input space. A large number of simulations are run to collect sufficient samples. There are two principal types of global methods: linear regression (Pearson, Spearman, and derivatives as SRC – Standard Regression Coefficient- and PRCC - Partial Rank Correlation Coefficient) and variance decomposition indices (Sobol).

SRC and PRCC are commonly used in building simulation sensitivity analysis. Domínguez-Muñoz undertook an SRC sensitivity analysis on peak cooling loads calculations to identify the inputs for uncertainty analysis [9]. Breesch and Janssens [10] performed a

global sensitivity analysis by calculating SRC coefficients after performing a Monte Carlo experiment.

Sobol indices can be calculated when the physical model computing time is low, after having eliminated the less influential parameters with local or screening methods. Faure [11] used the FAST method to compute those indices in a hybrid model of building envelope to measure the impact of input parameters on the internal volume temperature of a solar collector. Spitz [12] compared FAST and Monte Carlo sampling methods to get Sobol indices to identify the impact of the inputs: FAST is faster and more accurate than the sampling method but harder to implement. Goffart [13] calculated Sobol indices using the Mara sampling method [14] to determine the most influential inputs of a dynamic thermal simulation model. Berthou [15] computed those indices using a Latin Hypercube sampling method, in the validation step of its gray-box model of the building to check the validity of input parameters.

When a complex model requires a large number of input parameters, screening methods are intended to analyze the building model quickly, in order to eliminate non-influential inputs. Screening methods do not require entering inputs as distributions, but discrete levels. The most well-known screening procedure is the Morris method. De Wit [16] and Heo [17] applied Morris method as a preliminary stage to remove the least influential inputs. Bertagnolio [18] and Robillart [19] also employed this method as an upstream study to retain influential inputs to calibrate a building model.

Screening methods provide qualitative analysis of the inputs influencing one output and are often used before uncertainty or sensitivity analysis to exclude negligible inputs. Local sensitivity analysis focuses on the impact of the inputs on a target area of the input space. Global methods give more accurate results but require a larger number of simulations. It is therefore advisable to couple screening methods with uncertainty propagation analysis or to use them for sub-parts of a global building model.

1.2. Uncertainty analysis

Uncertainty propagation in numerical models assesses the consequences of a lack of knowledge about the input parameters on model outputs. There are two principal types of uncertainty analysis methods: local approximations (Taylor decomposition) and sampling methods (for instance: Monte Carlo, Latin Hypercube Sampling). The latter alone provides a full distribution of the quantity of interest.

Taylor decomposition is a simple method that cannot be used in the case of a very non-smooth model because of the risk of having inaccurate approximations and incorrect results. Brohus [20] applied Taylor decomposition to determine the uncertainty of heat losses through natural ventilation by coupling the local sensitivity method with a CFD model. These results are compared with a Monte Carlo approach, and there is no significant difference.

The Monte Carlo method is broadly used in the building field to achieve the propagation of uncertainty by analyzing distribution or dispersion. Macdonald [21] compared standard Monte Carlo methods stratified and Latin Hypercube applied to dynamic thermal simulation models. He concluded that Latin Hypercube Sampling is more robust than the Monte Carlo method and does not present any bias of sampling. Merheb [22], Eisenhower [23] and Goffart [13] performed building and weather uncertainty propagation studies using Energy Plus software. Parys [24] used the Monte Carlo method to model occupant behavior.

This overview shows that numerous methods are used to study the uncertainties of building envelope, weather, and occupant behavior and, to a lesser extent, to HVAC systems.

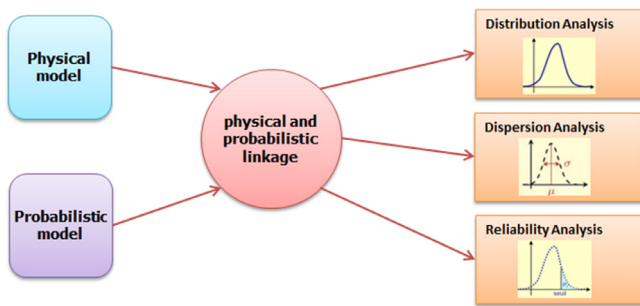


Fig. 1. Uncertainty methods.

2. Selection of methods

This section shows what the information provided by the identified methods is and how to classify them. The aim is to select which statistical methods can be used for an EPC.

Then, the selected methods are tested (part 3) on an office building to compare the computation time and the provided results.

2.1. Identified methods

The three different objectives of applying uncertainty methods to physical or statistical models are identified below (Fig. 1): distribution, dispersion and reliability analysis.

- **Distribution analysis** gives the full distribution of the variable of interest.
- **Dispersion analysis** provides mean, variance and moments of superior orders (kurtosis, skewness).
- **Reliability analysis** sets the probability of exceeding a threshold (a failure probability); these methods are not frequently used in thermal building studies.

These three objectives are relevant to establishing an EPC. Fig. 2 shows how the identified methods can be applied to reach these objectives and how to perform a sensitivity analysis. The methods reported in Fig. 2 are applied in the next part of this paper. Once the parameters of the study are selected by a screening or a local sensitivity method, a path will be chosen depending on the objectives. If a global distribution of the output is required, only sampling methods will be appropriate. If a quick assessment of the mean and standard deviation of the model is required, local sensitivity analysis will be selected.

2.1.1. Screening methods

If a hypothetical building model contains more than 50 inputs, the first step of the process is to reduce the number of these inputs by applying a screening method that scans the input area to remove the ones that are least influential. Two methods, the Morris and the Cotter, have been identified.

Morris method consists of randomly repeating r times an OAT-style (One at a time) experiment. Each input is discretized into some levels depending on the number of repetitions. This method requires $r \times (p + 1)$ simulations, with r being the number of iterations of the OAT experiment and p , the number of parameters [25]. Morris is a robust method that requires few assumptions about the inputs. The number of iterations is generally between 10 and 40 [26]. Thus, the number of required simulations is low compared to other global sensitivity analysis methods such as Sobol indices.

Cotter's method requires $2p + 2$ experiments (p being the number of parameters) and consists of testing the model by setting each parameter to maximum or minimum levels [27]. This method provides a quick estimate of the parameters' effect on the model

but can undervalue some effects and can lead to misinterpretations of the results. For instance, two factors with opposite sign effects may cancel themselves out, regardless of their importance [28]. Since this method can miss significant parameters, this method is discarded.

Only the Morris method will be tested and compared to Quadratic Combination (part of the approximation methods that lead to importance factors - see Fig. 2) to understand how these methods complement each other and to suggest when to use it during the development of the EPC.

2.1.2. Approximation methods

There are three families of Approximation methods:

- Quadratic Combination that gives both sensitivity (importance factors around the mean) and moments
- The First Order Reliability Model and the Second Order Reliability Model (FORM and SORM) that set failure probability (probability to exceed a predefined threshold) and sensitivity analysis around the threshold
- Regression methods that provide sensitivity and input correlation information

Quadratic combination: Quadratic Combination is based on the law of total variance which states that the variance of a random variable can be expressed as a function of its depending variances. To do that, the model is locally linearized by a Taylor expansion to first or second order, and then the total variance law is applied. This method is suggested in the Guide to the Expression of Uncertainties Measurements [29] to conduct uncertainty analysis. To compute sensitivity indices, it is necessary to assign to each input parameter a nominal value around which it will vary. The difficulty of this method lies in the determination of partial derivatives and may require considerable time to calculate. The model must not have any significant non-regularity, or the variation tolerance must not be too high [30] to justify the Taylor approximation. Nevertheless, Quadratic Combination can quickly produce a dispersion analysis only requiring the mean and the covariance matrix of the inputs. Quadratic Combination also provides importance factors with only $2p$ simulations (p being the number of parameters).

FORM and SORM methods: FORM and SORM methods assess the failure probability and the sensitivity analysis of the parameters near the failure point. The failure plan is considered as a half-plane (FORM) or quadratic surface (SORM). The approximation is theoretically verified if the failure plan is linear (or quadratic) in physical space and if the input variables are normal. The further the study is from these assumptions, the worse the approximation [31]. The advantage of FORM and SORM is that calculation time is reduced compared to other simulation methods. Computing time is the same regardless of the desired precision of failure probability. Nevertheless, the approximation is not always accurate, and the physical model has to be differentiable. FORM and SORM methods are the only ones that provide the failure probability without having to study all the input space.

Regression methods: Regression methods require the model to be linearizable in order to get an acceptable approximation. The model needs at least $n + 1$ simulations, with n being the number of inputs. Before using regression methods, it is necessary to check if the model is linear. If so, Pearson's Correlation Coefficient (CC), PCC (Partial Correlation Coefficient) and SRC (Standardized Regression Coefficients) are usable. If the model is not linear but monotonous, Spearman's Correlation (SC), SRCC (Spearman Rank Correlation Coefficient), PRCC (Partial Rank Correlation Coefficient) and SRRC (Standardized Rank Regression Coefficients) are adapted [32]. If the model has non-linear and non-monotonous trends, regression methods cannot be employed.

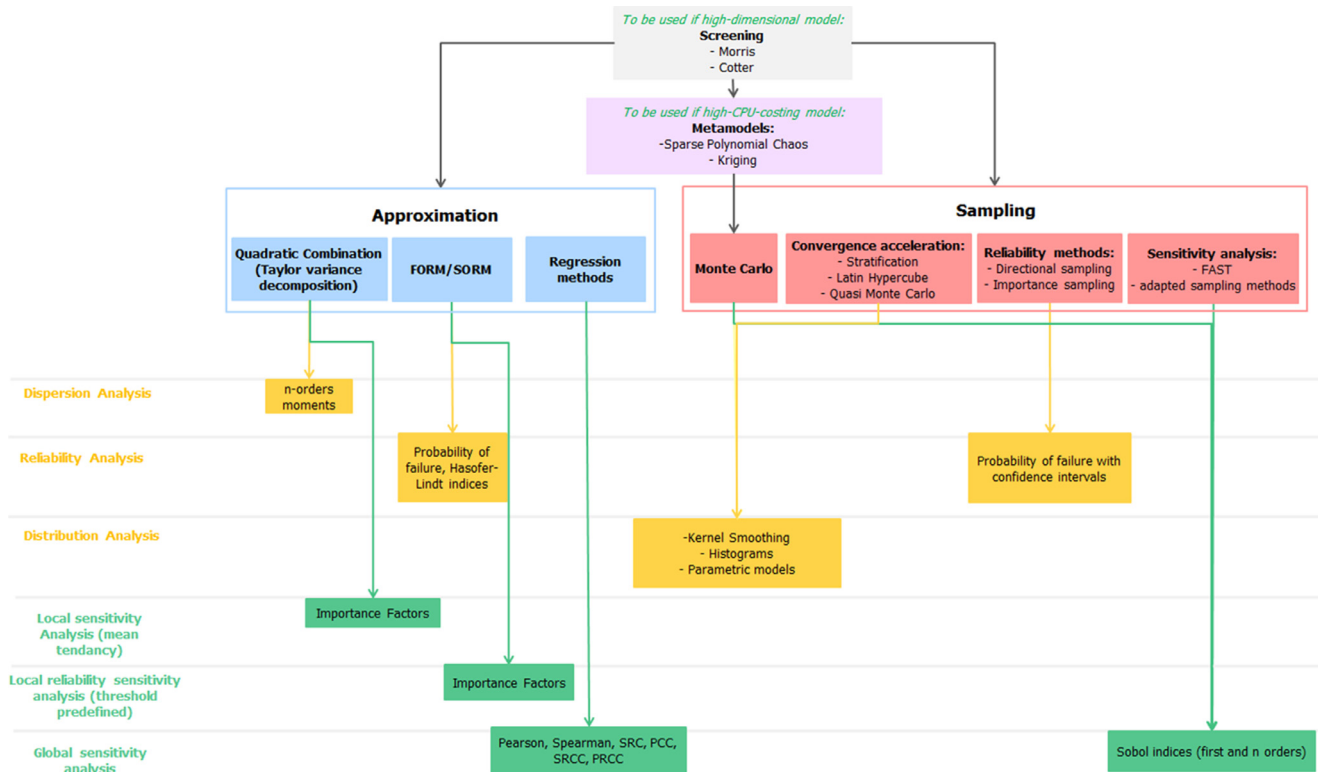


Fig. 2. Global uncertainty and sensitivity analysis literature review.

2.1.3. Sampling methods

Sampling methods consist in carrying out a large number of simulations using different ways to create the input samples. Monte Carlo is the most common because the samples are generated randomly. However, the major disadvantage of this model is the computation time needed. In order to obtain an output distribution, numerous random simulations of the model have to be carried out, which can be very time-consuming for complex models [33].

Convergence acceleration sampling methods: Convergence acceleration sampling methods can be used. Sampling is not random but generated according to the following rules:

- **The Stratification** method consists of partitioning the support of the input distributions into disjoint sub-domains with equiprobable intervals. Then, a random selection is performed inside the sub-domains.
- **The Latin Hypercube** method is like stratification, except that the points are not selected in each stratum but a subset, such that no pair of subassemblies should have the same value for the same parameter [21].
- The principle of the **quasi-Monte Carlo** method is to replace random sequences of Monte Carlo methods by low discrepancy sequences, built deterministically to present a low dispersion. There are several standard low discrepancy sequences, such as Halton, Faure or Van der Corput sequences [28].

Reliability methods: Reliability methods allow us to compute the probability of exceeding a predefined threshold. The other sampling methods (Stratification, Latin Hypercube, and Monte Carlo) offer reliability results too. Some methods have been specially developed to target the failure space.

- **Importance sampling** consists of replacing the initial input probability density by a more efficient one regarding failure and then centering the sampling around the failure field [34].

- **Directional Sampling** provides an estimate of the failure probability by cutting input space into quadrants [35]. This method randomly probes the input space among several radiations and directions.

Both methods will be tested.

Sensitivity analysis methods (variance decomposition): Variance decomposition methods consist in creating numerous samples to compute sensitivity indices all over the input space. Sobol indices are calculated as part of the variance. Saltelli and Chan [5] created total indices that allow us to compute the global impact of a parameter, including its interaction with other parameters. The FAST method suggests decomposing the variance using Fourier transformation. The general concept of the method is based on the idea that the oscillation of the response of the model around its natural frequency will be influenced by the natural frequencies of the inputs. The more influential an input, the more it will impact the oscillation of the response [35]. Computing Sobol indices using sampling or FAST methods are too time-consuming to be tested in a building model, but they can be used for local studies.

2.1.4. Metamodels

Metamodels replace the physical model by running a swift code that performs a building simulation in less than one second. A standard thermal dynamic model takes more than a minute.

Polynomial chaos expansion consists of the projection of the model output onto the basis of orthogonal polynomials in the input space [36]. This allows us to represent the model output variability with regard to the inputs. Sparse chaos expansion projects the model output onto an adapted basis in which only the most significant coefficients will be taken into account to reduce the cost of the metamodel creation procedure [37].

The Kriging metamodel, also known as “Gaussian process” is a model interpolating the responses as a mapping: the model performs a linear combination of the data, taking into account the

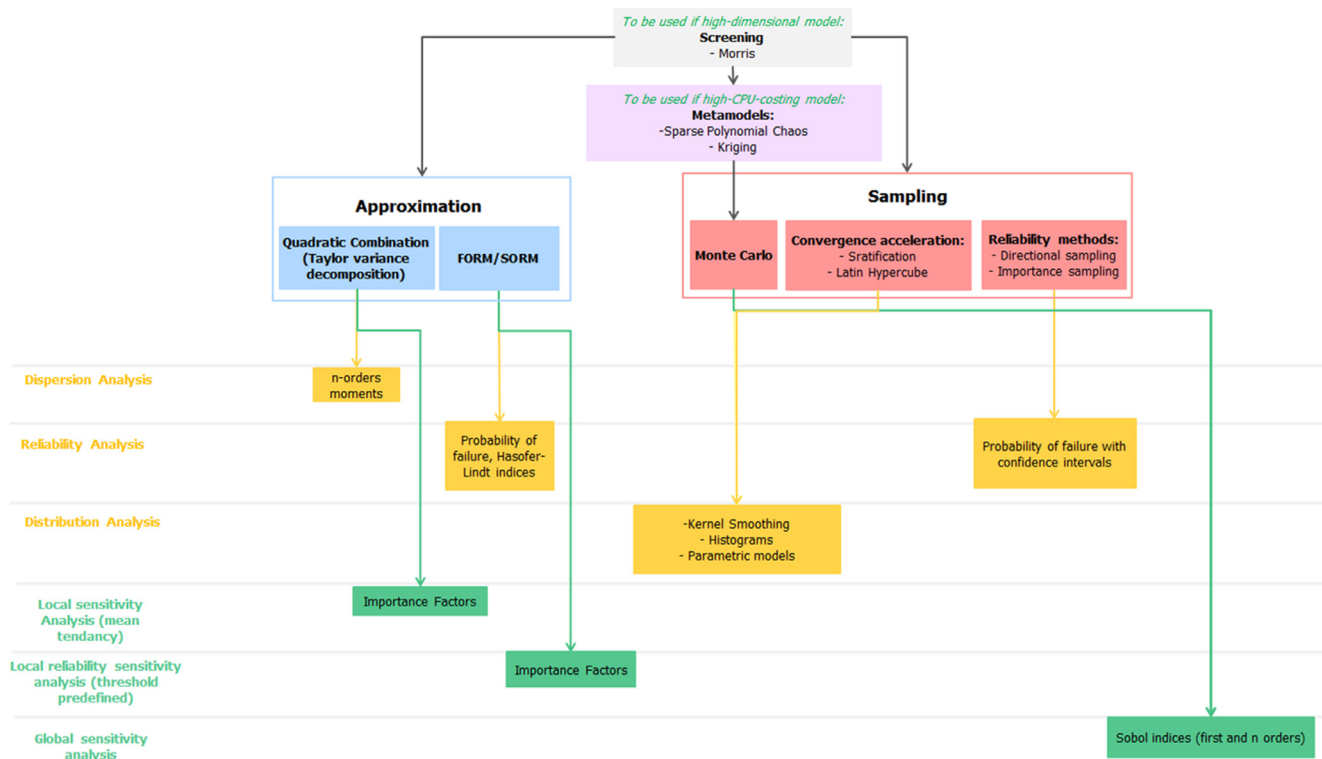


Fig. 3. Selected methods for uncertainty and sensitivity analysis.

distances between data and results. Sparse polynomial chaos expansion and Kriging are compared.

2.2. Selected methods to be tested

Given the review carried out, the selected methods, which will be numerically tested in a study case, are shown in Fig. 3.

3. Case study description

3.1. Building description

The case study is a 4000 m², two-floor office building in Nantes (West of France). It has the following characteristics:

- 2 air handling units (AHU) to ensure indoor air quality:
 - 1 for the ventilation of the offices (chilled beam) and the storage zones.
 - 1 for the showroom areas
- 2 reversible Heat Pumps:
 - North: supplies 3 networks, underfloor heating systems, north chilled beams (ground floor) and AHUs
 - South: supplies ground and first-floor chilled beams.

The thermal zoning is shown in Annex 1.

3.2. Probabilistic model

The study focuses on 49 uncertain parameters of the building and its systems: AHUs, heat pumps, water networks, building walls, building glazing, infiltration, ground exchanges, set points and occupancy.

Parameter selection followed 3 steps:

- **Pre-selection of physical parameters** according to the following considerations:

- Replace non-physical and discrete parameters with physical and continuous ones.
- Discard time-dependent parameters (such as weather temperature, occupancy scenarios) which should be preferably used as corrective factors of energy consumption based on real weather and occupancy data in the EPC process.
- Do not consider the parameters that are unlikely to be changed during the construction stage (building dimensions).
- **Parameter gathering:** this stage consists of identifying parameters that can be grouped. The idea is to use only one distribution for the regrouped parameters by using a coefficient that will multiply all the parameters of the group in the same way. A component which is used several times in the building, for instance, a pump, could be regrouped to get an overall effect instead of a component-by-component effect. Secondly, by considering the building commissioning procedures, one can define links between the uncertainties of some parameters. For instance, all the airflows are checked together, following a precise order. Thus, all the airflows from the same branch in a group can be gathered.
- **Parameter aggregation based on an upstream uncertainty study:** a global building simulation model is composed of sub-modules which can be run independently. Thus, instead of considering each parameter as an input for the global building simulation model, the user can perform several upstream local uncertainty analyses and then use the result as an input of the global model. To maintain the independence of the parameters, the parameters used in the local models cannot be considered as inputs to the global model. Rivalin et al. [38] presented a method to aggregate fan parameters into a single uncertain variable.

The selected parameters are the following (see Table 1):

Table 1
Uncertain Input parameters for the case study.

Category	Number of parameters
AHUs	11
Heat pumps	8
Water networks	16
Building walls	2
Building glazing	2
Infiltrations	1
Ground exchanges	1
Set points	5
Occupancy	1
Lighting	1
Equipment	1
Total	49

Since the heat pumps are generally modeled in building energy simulation tools by using performance as functions of outside temperature, a specific methodology has been used to define the uncertainties. To take into account the uncertainties of the heat pump performance variation with outside temperature, the performance matrices (the capacity of the heat pump and Coefficient Of Performance) have been linearized, and the uncertainties have been applied to each coefficient of the two linear regressions.

The source of the mean values is the manufacturer's catalogs (for energetic facilities) and architects (building geometrical and thermal data). The occupancy data comes from the client or are assumptions. Three types of probability density are chosen to characterize the parameters, depending on the knowledge accorded to the parameters: the amount of confidence is reflected by the distribution's width.

- **Uniform (min, max) distribution:** min and max are the minimum and maximum values that an expert can suggest for this parameter. This distribution should be used when there is an equal probability that the "true" value is situated between the bounds. Uniform distribution will also be used for inputs related to the behavior of the occupants.
- **Beta (mean, standard deviation, min, max) distribution:** This asymmetrical distribution will be used when the data comes from manufacturer catalogs; it is assumed that a margin of error has already been taken into account when the data is supplied. This distribution is appropriate if the data is considered as "optimistic" or "pessimistic".
- **Truncated Normal (mean, standard deviation, min, max):** Normal distributions are truncated to prevent outputs from tail bounds of the distribution causing incorrect results. This distribution is used when the parameters are not from catalogs but can be measured during the commissioning process (airflows, for example).

The selected input distributions are detailed in [Annex 2](#).

3.3. Experimental environment

Several sensitivity and uncertainty analysis methods identified in Part 2 are studied here. In this case study, there is only one output studied which is the total annual electricity consumption of the building and its systems (heat pumps, pumps, fans, lighting, and equipment). This model does not contain any discrete variables.

The thermal simulation of the building is carried out on TRN-SYS17 [39] and runs for 11 min (1-h time step for a year simulation) in a workstation equipped with an Intel Xeon chip with 8 CPU cores (16 threads) E5-2637 CPU 3.5 GHz.

The statistical methods described part 2 are implemented in Python libraries like OpenTURNS [40], used to perform the analyses of this paper. Commercial tools such as Optimus by Noesis

Solutions [42] or PhimecaSoft [43] offer several of the suggested methods wrapped in a graphical user interface.

For this study, statistical experiments have been programmed in Python 2.7, using the OpenTURNS library in particular [40] that offers many uncertainty and reliability methods as well as efficient coupling tools for TRNSYS. The program is parallelized 16 times achieving as many simulations as processors. To do that, the joblib package is used, included in the scikit-learn library [41].

Screening and local sensitivity methods are first applied to reduce the number of parameters. Then, distribution and dispersion analysis are applied to get the moments. The next steps consist in comparing several reliability methods and then applying sensitivity results. Finally, 2 metamodels (Kriging and sparse polynomial chaos expansion) are studied.

4. Results and discussion

4.1. Screening methods

Screening methods are performed as a preliminary test to the sensitivity and uncertainty analyses. It helps to avoid studying non-influential parameters by reducing the dimension of the study.

Morris method implementation requires choosing the number of repetitions of the OAT design of experiments (doe).

$r \times (p + 1)$ simulations are necessary to obtain the relative sensitivity of the parameters, r being the number of OAT doe and p , the number of inputs. Given the study of Ruano et al. [26] and the length of the simulations, $p = 10$ will be chosen.

Morris method is compared to a simple local sensitivity analysis method: The Quadratic Combination which is very quick because it requires only $2 \times p$ building simulations. This method consists of assessing the sensitivity of every parameter close to its average, close to $0.5 \times \sigma$, σ being the standard deviation. This 49-parameters study required the following computation times, see [Table 2](#):

Table 2
Local sensitivity method times.

Method	Number of simulations	Calculation time (by parallelizing on 16 threads)
Quadratic Combination	98	52 min
Morris R = 10	500	4h 05 min

Morris method provides, the following values for each parameter: σ (standard deviation of the elementary effects, representative of the interaction and linearity effect of parameters) and μ^* (the mean of the absolute value of the elementary effect: representative of the importance on the output) (see [Fig. 4](#)).

The ranks obtained by the Morris method or Quadratic Combination (see [Fig. 5](#)) are very similar, except for slight changes between groups, but Quadratic Combination requires 4 times less calculation than the Morris method.

The Morris method provides additional information such as the detection of non-linear effects of the parameters and the interactions between factors. Yet, this information is known a priori when the user builds its own model and the input distributions. Thus, the extra time needed for the Morris method does not seem justified in this case. Therefore, it is preferable to use a quick method for local sensitivity analysis to quickly identify the parameters to retain for the uncertainty analysis.

However, if the model contains parameters with very non-smooth effects (for instance, threshold effects correlated with several input parameters), the Quadratic Combination is not appropriate anymore, so Morris method is recommended to select the most influential input parameters. [Table 3](#) summarizes the advantages and limitation of using either Quadratic Combination or Morris method.

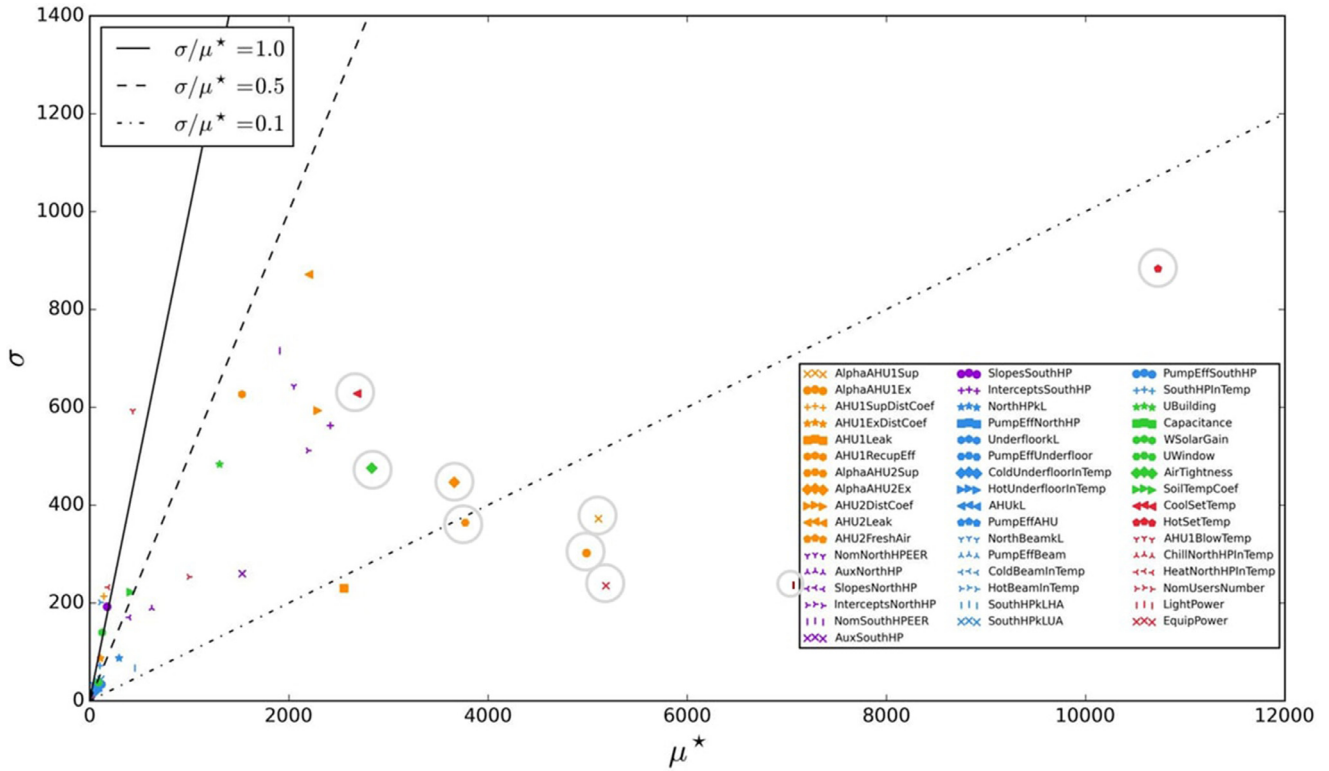


Fig. 4. Morris results (the parameters in the legend are described in Annex).

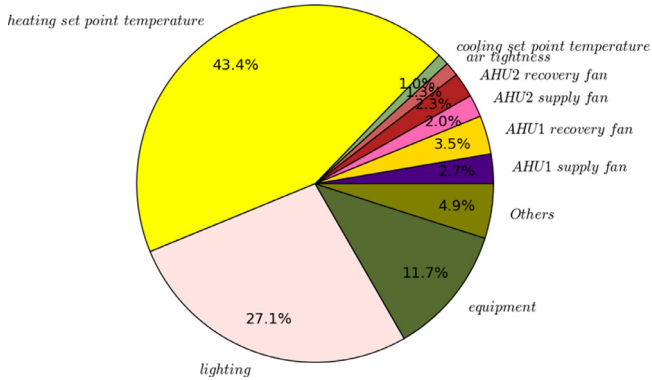


Fig. 5. Importance Factors obtained by Quadratic Combination.

Even if it is obvious that 9 parameters are really important (circled on Fig. 4.) and would be enough to pursue the study, the 24 most influential inputs will be selected to lead a study as complete as possible. This allows us to test the robustness and accuracy of the probability algorithm with more than 20 parameters. Moreover, Crestaux [36] showed that polynomial chaos expansion is limited to a moderate number of inputs (less than 20). We would like to check if in this case, the LARS (least-angle regression) algorithm

used to create a sparse polynomial chaos expansion allows us to overcome this and study a model with more than 20 inputs.

The parameters that are selected are the followings, ranked by importance:

- 1) Heating set point temperature [18–22 °C]
 - 2) Lighting power multiplier [0.9–1.1]
 - 3) Equipment power multiplier [0.9–1.1]
 - 4) Supply fan power of AHU 1 (by introducing an aggregated parameter built from an upstream uncertainty analysis)
 - 5) Extract fan power of AHU1 (by introducing an aggregated parameter built from an upstream uncertainty analysis)
 - 6) Supply fan power of AHU2 (by introducing an aggregated parameter built from an upstream uncertainty analysis)
 - 7) Extract fan power of AHU2 (by introducing an aggregated parameter built from an upstream uncertainty analysis)
 - 8) Air tightness of the building [1.5–1.7 m³/h/m²]
 - 9) Cooling set point temperature [25–27 °C]
- Beyond those 9 parameters, the following represent less than 1% of the effects on the output.
- 10) Air leakage of AHU 1 coefficient [0–0.2]
 - 11) South HP matrix performance (by introducing a corrective factor) [0.8–1.1]
 - 12) Airflow distribution parameter AHU 2 [–0.2–0.2]

Table 3
Quadratic combination and Morris advantages and limitations.

Method	Quadratic combination	Morris
Family	Local approximation	Screening
Quick computing method	X	
Can detect non-linear effect and interactions between factors		X
Can be applied to non-smoothed model		X
Other comments	The method focuses on the impact of the inputs on a target area of the input space.	The results depend on the number of iterations of the OAT design of experiment and can differ from one experiment to another.

- 13) Air leakage of AHU 2 coefficient [0–0.2]
- 14) North HP matrix performance (by introducing a corrective factor) [0.8–1.1]
- 15) Nominal North Heat pump EER [2–3]
- 16) Nominal South Heat pump EER [2.7–3.6]
- 17) Auxiliary electric power coefficient of South HP in cold and hot modes [0–2]
- 18) Heat recovery efficiency of AHU1 [0.65–0.8]
- 19) Building heat loss multiplier [1–1.2]
- 20) Nominal user number multiplier [0.8–1.2]
- 21) Auxiliary electric power coefficient of North HP in cold and hot modes [0–2]
- 22) Total thermal capacitance of zones (air plus any mass except walls) [500–1000 kJ/K]
- 23) Blowing set temperature of AHU 1 [15–17 °C]
- 24) Overall South HP network losses coefficient in unheated area [0.0013–0.007 kW/K]

Morris methods and Quadratic Combination allow us to identify, for any physical models in various domains, what the most important parameters are. The previous ranking may be very different for other types of buildings, with different size, systems, climates and in other sectors. The ranking also depends on the “confidence” of the input data, traduced by the input distributions width of each parameter; the larger the distribution will be, the more it might impact the output.

4.2. Distribution and dispersion analysis

Now that the number of parameters has been reduced from 49 to 24, a propagation of uncertainty is performed to obtain the distribution and dispersion of the response. Sampling methods are the only ones that can offer the entire distribution of the output. These methods are used to determine from scratch a consumption threshold for the contract.

Sampling method computational time does not depend on the number of inputs but the required output precision. To obtain distributions and dispersions, the central tendency (mean and standard deviation) is studied by the comparison of two methods: the “standard” Monte Carlo method and Latin Hypercube. We wanted to obtain a mean estimation with a relative error of the order of magnitude of 10^{-5} . The resulting annual consumption will be plotted by kernel smoothing overlaid over the histogram.

Monte Carlo required 1408 simulations to reach the awaited precision, whereas Latin Hypercube required 448 simulations. The obtained results are shown respectively in Figs. 6 and 7.

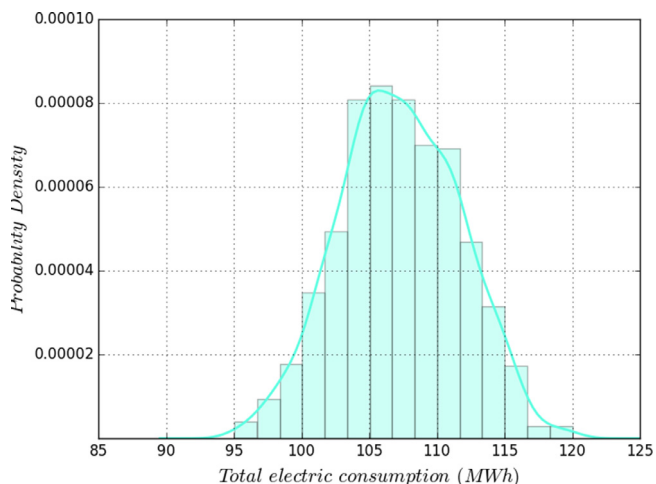


Fig. 6. Distribution of total electric consumption obtained with Monte Carlo after 1408 simulations.

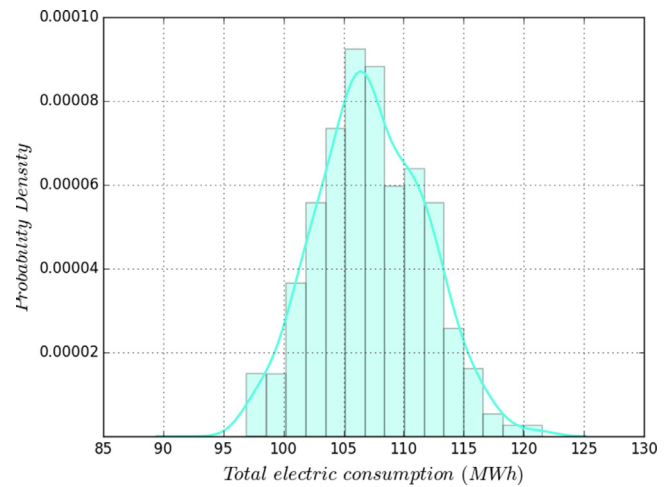


Fig. 7. Distribution obtained with Latin Hypercube after 448 simulations.

In this case, Latin Hypercube allows us to obtain a full distribution of the output in less time than Monte Carlo. It should be noted that sampling methods also allow us to obtain the results of several outputs simultaneously. By reading the distribution graph, a consumption threshold can be assessed.

The Quadratic Combination method provides first order moments, with $2 \times p$ (p being the number of parameters) simulations: mean and standard deviation. However, the method cannot give the total distribution. This method cannot take into account discrete parameters. Unlike sampling methods, the experiment has to be repeated as many times as there are outputs and discrete parameters levels to study. Nevertheless, this method offers a reasonable estimate of the mean and standard deviation with a few simulations, provided the model does not have any significant non-smoothness (as this is the case here), see Table 4.

Table 4
Dispersion analysis method comparison.

	Monte Carlo	Latin hypercube	Quadratic combination
Mean	107.2 MWh	107.3 MWh	107 MWh
Standard deviation	4.43 MWh	4.46 MWh	4.46 MWh
Number of simulation	1408	448	48
Simulation time	13 h 38'	3 h 54'	25'

To conclude, Latin Hypercube and Quadratic Combination methods are complementary and employed depending on the desired objective: fast and straightforward moment estimation or full distribution analysis. The Quadratic Combination provides a reasonable estimate of the mean and an order of magnitude of the standard deviation. This method is beneficial to identify an energy consumption threshold quickly. For instance, it is possible to set the threshold to the mean plus 3 or 4 times the estimated standard deviation. Unlike the Quadratic Combination method, the sampling methods allow us to get the overall output dispersion, to study several outputs simultaneously and to include discrete parameters. Latin Hypercube is always preferable to standard Monte Carlo since it can describe the entire input space and converges more quickly.

Thus, in the case of a smooth model with a few discrete parameters, Quadratic Combination will be used to assess the central tendency. If the probabilistic model contains several levels of discrete parameters, and multiple outputs are to be studied, the Quadratic Combination method will be performed as many times as there are outputs and discrete levels. In this case, the Quadratic Combination method for smooth models loses its appeal if the model presents over 9 levels of discrete parameters or outputs to study.

This study has been performed on the 24 selected parameters. Sampling methods' (Monte Carlo and Latin Hypercube) computa-

Table 5
Quadratic combination and sampling methods advantages and limitations.

Method	Monte Carlo	Latin hypercube	Quadratic combination
Family	Sampling method	Sampling method	Local approximation
Simulation time	13 h 38'	3 h 54'	25'
Can be applied to non-smoothed model	X	X	
Can provide the overall output distribution	X	X	
Can provide the results of several outputs simultaneously and study discrete parameters	X	X	
Can be applied to non-smooth models	X	X	
Other comments	This is a random sampling: some area of the input space may not be represented		

tional time is not linked to the number of parameters. Thus, adding the 15 extra variables did not impact the total computational time, and slightly improved the accuracy of the results. Nevertheless, setting up the 15 extra parameters requires a few hours' work, and then the minimal accuracy provided by these parameters complicated the analysis unnecessarily. Moreover, as Quadratic Combination's computational time is directly linked to the number of parameters – the result is provided after $2 \times p$ (p being the number of parameters) simulations, using the 15 extra parameters will increase the computational time without significantly improving the accuracy of the results. Thus, in a real case, only the 9 main parameters would have been used, see Table 5.

4.3. Reliability methods

Reliability methods compute the probability of exceeding a given threshold. These methods can be useful in the context of an EPC to characterize and optimize an existing threshold. This kind of situation occurs in the case of a massive retrofit or the accordance of an energy performance label. This method is also useful when the threshold has been set according to an approximation method, to check the result. To be consistent with the overall uncertainty comparison, we decided to set the threshold arbitrarily to 115 MWh, regarding the previous dispersion.

This study aims to identify reliability methods where overall computational time is less than 24 h.

Sampling methods are useful to compute the probability of exceeding a threshold by calculating the ratio between the total number of simulations and the number of simulations in the failure space. Monte Carlo or Latin Hypercube allow us to do this. However, the more precise the failure probability, the longer the computational time. This is why reliability methods, such as directional sampling, importance sampling, and Quasi-Monte Carlo, based on the sampling optimization have been created. Every sampling method provides a confidence interval around the obtained results, except Quasi-Monte Carlo which is not a random sequence.

Directional Sampling requires a preliminary isoprobabilistic transformation. The transformed input random variables are independent, standard Gaussian variables (mean=0, standard deviation=1). This method consists of randomly scanning the input space by radius and assessing the intersection of each direction with the boundary of the failure space, to take into account the contribution of the new direction towards the probability of exceeding the threshold. Therefore, each step of calculation depends on the previous time step. Thus, it is not possible to carry out the processes simultaneously. As a consequence, this method is very time-consuming. Still, it has been tested to check if the time gain makes it competitive with a conventional method distributed over 16 processors. After 24 h, that is to say, more than 100 simulations, the model did not converge.

Importance Sampling requires replacing the initial distribution by another one that will quickly approach the failure space. To do that, an importance distribution is created to generate new sam-

ples. The major drawback of this method is the fact that it is not easy to know before the experiment how to create an importance distribution. This method will be coupled with FORM to determine an importance distribution.

The reliability approximation methods are FORM and SORM. As for the Directional Sampling method, it requires converting the input space into a standard one. Then, the probability of failure is approached by a half-plane (FORM) or by a quadratic surface (SORM). The distance between the origin of the standard space and the nearest limit point of the failure space from the origin is assessed using an optimization algorithm and provides the threshold exceedance probability.

FORM's advantage is the quick computational time, but it does not deliver the result of the confidence interval. As mentioned before, we suggest coupling FORM method with importance sampling to define the importance distribution as a normal distribution centered on the standard point of failure calculated in FORM method and to get the interval of confidence of the output. SORM has the same disadvantages as FORM method and moreover requires, in this study case, 13 times more simulations than FORM to converge. SORM can be very useful when the limit state function has to be known accurately to apprehend small exceedance probability (as in nuclear safety, typically). In this case, it is not necessary to consider probabilities lower than 0.1%. Table 6 shows the result of the comparison performed with the methods presented above with a 115 MWh threshold and a coefficient of variation of the desired confidence interval of 0.1.

All reliability methods' computational times are not linked to the number of inputs. Thus, as previously, adding 15 extra parameters does not impact the total computational time but unnecessarily complicates the study.

To conclude, when only a threshold exceedance probability is required, FORM method is recommended. Even if FORM method overestimates the results compared to the other methods, it provides an order of magnitude of the failure probability at least 13 times faster than the other methods with a 30% error. Coupling FORM method with importance sampling makes it possible to obtain the confidence interval of the result still faster than other sampling methods (Table 7).

4.4. Sensitivity analysis

Given the computational time of one simulation (11'), approximation methods cannot be compared to sampling sensitivity analysis methods. Indeed, computing Sobol indices would require around 24,000 simulations to study the selected parameters, that is to say, several weeks of computational time.

FORM Importance factors are calculated with a threshold of 115 MWh (see Fig. 8):

Importance factors help identify the uncertainty due to the parameters in the failure probability. Thus, the result of this method is different in nature from Quadratic Combination's importance factors. We can see that the group of nine most influential factors

Table 6
Reliability methods comparison.

	Probability of exceeding the threshold	Confidence interval	Number of simulations	Simulation time
Monte Carlo	4.55%	[3.6%; 5.3%]	2272	22 h 54'
Latin hypercube	4.7%	[3.8%; 5.7%]	2048	19 h 55'
Quasi-Monte Carlo	4.2%	–	2160	21 h
Directional sampling	No convergence after 24 h of simulations			
Importance sampling (+ FORM)	4.6%	[3.8%; 5.4%]	1312	12 h 43'
FORM	6%	–	100	58'
SORM	5.3%	–	1301	12 h 32'

Table 7
Reliability methods advantages and limitations.

	Family method	Simulation time	Delivers a confidence interval
Monte Carlo	Sampling	22 h 54'	X
Latin hypercube	Sampling	19 h 55'	X
Quasi-Monte Carlo	Sampling	21 h	X
Importance sampling (+ FORM)	Approximation, then Sampling	12 h 43'	X
FORM	Approximation	58'	
SORM	Approximation	12 h 32'	

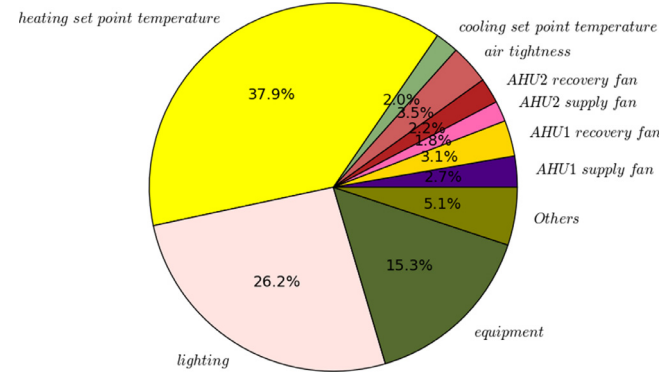


Fig. 8. Importance Factors obtained by FORM in the neighborhood of the consumption threshold (115 MWh).

is exactly the same in the neighborhood of consumption threshold (115 MWh). As the FORM method’s cost is low, it can be applied to different consumption thresholds to study the evolution of the share of responsibility of the parameters in the probability of exceeding given thresholds.

4.5. Metamodels

The application of several sampling methods in the previous parts showed that the total calculation time to get the output distribution (total annual consumption) or the probability of exceeding a threshold is very high. Global sensitivity methods cannot be directly used on the building model because the computational time is more than a week.

One solution is to approach the physical model built in TRN-SYS with a much faster model constructed by analyzing the effect of the random input variables on the outputs. This approximate model can then be used to apply all the methods already studied previously but in a reduced time. Two metamodel families can be adapted to this study case: Kriging and Sparse Polynomial Chaos Expansion. Kriging metamodels is a geostatistical method, used to interpolate the response of the physical model and assess its uncertainty, using a spatial basis. Polynomial Chaos expansion consists of the projection of the model output on a basis of orthogonal polynomials in the input space [36]. Thus, the model output

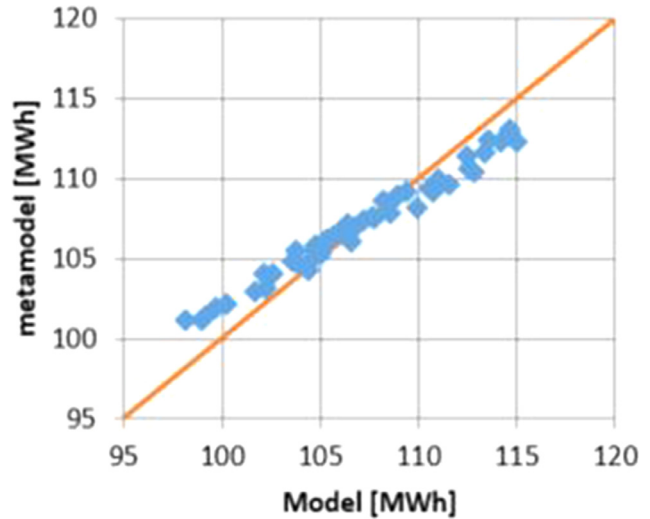


Fig. 9. TRN-SYS model and Kriging metamodel comparison.

variability can be represented with regard to the inputs. The construction of the sparse Polynomial Chaos basis is made thanks to the LARS (Least-Angle Regression) that consists of identifying the most significant polynomials, and not all the terms of all the polynomials [37]. Both of these metamodels are unique in being able to facilitate Sobol indices calculations. The goal here is to compare and select one of these metamodels for the case study.

The accuracy of the built metamodels is characterized in two ways:

- Assess the **leave-one-out error** in the learning basis. The basis is divided into two partitions: (n–1) samples are used as the training set, and the nth remaining observation is the validation set. In this case, a 10⁻⁵ error is acceptable.
- Construction of a validation basis to compare the model and metamodel results. The **relative error** of a metamodel is computed as follows:

$$E = \max_N \left| \frac{M(X_i) - \hat{M}(X_i)}{M(X_i)} \right| \tag{1}$$

where E is the error, N the number of simulations in the learning basis, X_i the inputs of the simulation i, M(X_i) the result of the model for X_i, and $\hat{M}(X_i)$ the result of the metamodel for X_i. We decided to select a metamodel if its relative error is less than 10⁻². The validation or both metamodels includes the results of 50 building simulations.

4.5.1. Kriging metamodels

The metamodel created by Kriging requires us to know precisely the covariance matrix of the original model. Fig. 9 shows model and Kriging metamodel results (created from 1400 learning simulations) using 50 simulations for validation. The relative error calculated is 3.14 × 10⁻². The orange line corresponds to X=Y. It should be noted that the metamodel does not perfectly estimate

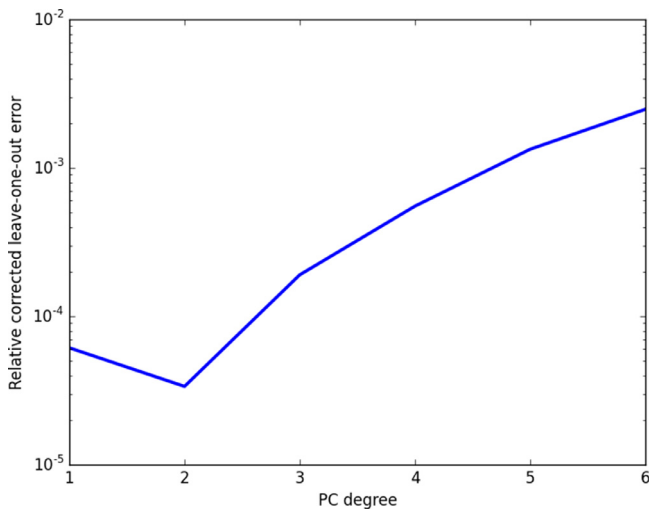


Fig. 10. Evolution of the metamodel leave-one-out as a function of the chaos polynomial degree.

the model. In fact, the metamodel shows a systematic bias increasing with the distance to the central value, although the validation procedure covers the same input and output space that the learning basis.

This bias is probably caused by an overfitting issue. Indeed, the leave-one-out error between the metamodel and model reached 10^{-30} . This problem occurs where there is a lack of data: the model predicts with high accuracy the available points, but provides an abnormal result between the learning-basis points. This result is due to the fact that, for a Kriging metamodel, 1400 data for a 24-dimension input space is not enough. So, another metamodel is tested: sparse polynomial chaos.

4.5.2. Sparse polynomial chaos

24 parameters have been selected to test if the polynomial chaos expansion method allows us to use more than 20 parameters.

The number of terms T of a polynomial, with p being the number of parameters and d the degree of the polynomial is:

$$T = \frac{(d + p)!}{d!p!} \tag{2}$$

Thus, the number of simulations necessary to create an accurate metamodel depends on the degree of the polynomials and the number of inputs. Nevertheless, the expansion in sparse polynomial chaos circumvents this problem by interpolating with fewer simulations than the number of terms to calculate. For example, in this case, with 24 parameters, beyond a sixth degree, the computer does not have sufficient memory capacity for calculating the coefficients of the polynomial.

Therefore, given the fact that we have to build a 24-parameter-metamodel, the time budget (number of simulations) is set to 200. Then, we search for the optimal degree of polynomial expansion to approach the model with 200 simulations in the learning basis. The relationship between the metamodel leave-one-out error and the polynomial degree is plotted Fig. 10.

Fig. 10 shows that the optimal degree is 2 and the leave-one-out error is 3.4×10^{-5} . To build a polynomial chaos expansion of a higher degree with a better accuracy, more learning simulations are needed.

Fig. 11 compares the model results (x -axis) to the metamodel (y -axis) for the approximation of the total annual electricity consumption, using 50 simulations for validation. It can be seen that the approximation of the physical model by the metamodel gives satisfactory results with a budget of only 200 simulations with

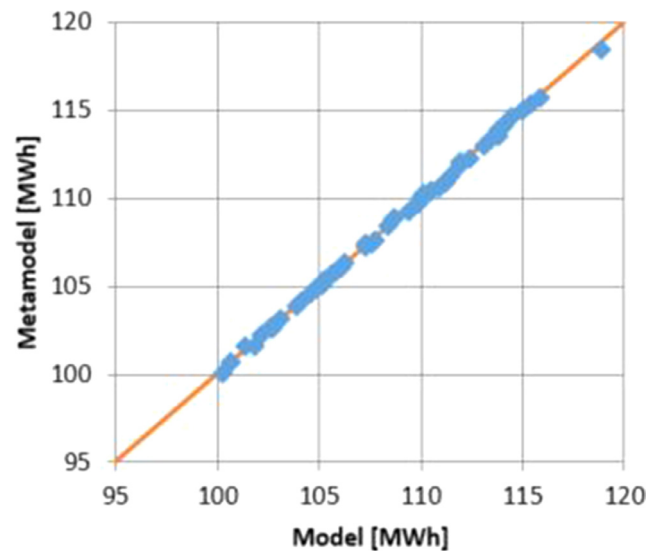


Fig. 11. Comparison of TRNSYS model and metamodel created by a sparse polynomial chaos expansion of degree 2, with 200 simulations.

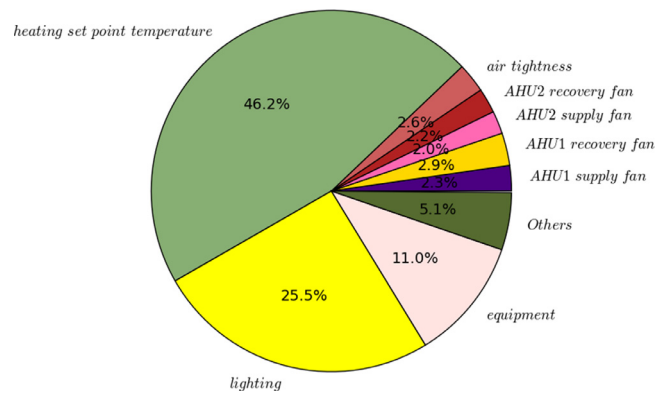


Fig. 12. Sobol indices obtained from sparse polynomial chaos.

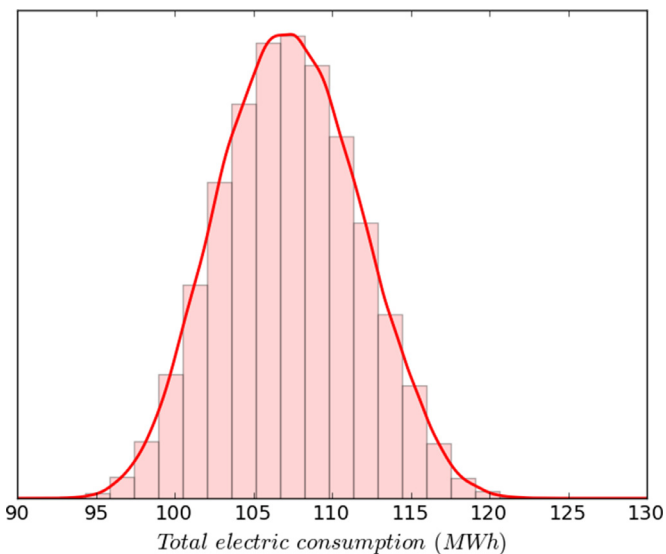


Fig. 13. Uncertainty propagation by Latin Hypercube obtained with the metamodel.

24 parameters. The relative error obtained is 3.27×10^{-3} , so the metamodel can replace the model. The $X=Y$ line is plotted in orange in Fig. 11.

One advantage is that determining the Sobol decomposition and sensitivity indices is immediate once the polynomial expansion of the model is known [36]. The first-order Sobol indices identify the

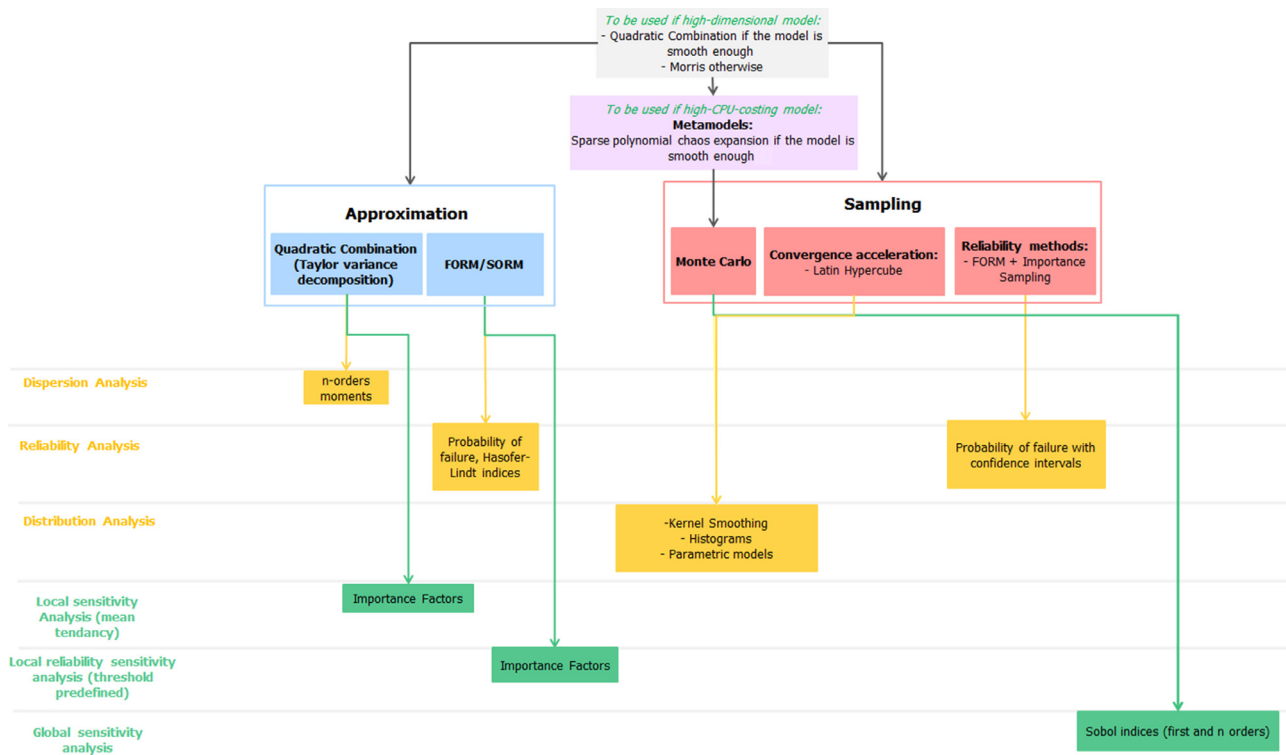


Fig. 14. Selected methods to guarantee a building's performance.

most influential model parameters. The degree 2 of the metamodel built from 200 simulations is used to compute indices Sobol and uncertainty analysis. Sobol indices obtained from the metamodel are given in Fig. 12.

Propagation of uncertainties obtained by Latin Hypercube thanks to the metamodel is given in Fig. 13.

Sparse chaos polynomial expansion allows us to approach a physical model in a very efficient way, with less than 500 simulations, depending on the number of parameters.

The approximation of a model by a sparse polynomial chaos works if the model is smooth enough with, for example, no threshold effects. The user a priori has a clue of the smoothness of the model since he generally builds the physical and statistical parts of the model. However, in some cases, the non-smoothness is not apparent, and the user may need to check it. Also, some threshold effects may exist in the model without making it completely non-smooth. Thus, the chaos polynomials method can be useful to quickly characterize the smoothness of the model, in a limited number of simulations.

5. Conclusion

In this study, several methods were studied to establish a consumption threshold in the framework of a building's Energy Performance Contract.

First of all, when the number of inputs is high, it is necessary to reduce it by identifying the most influential ones. Then, Quadratic Combination method is an appropriate solution to quickly identify sensitivities in the neighborhood of the average of the inputs. However Quadratic Combination is not appropriate for non-smooth models and does not provide information about the smoothness of the model. Thus, in the case of an inherent non-smoothness in the model, the Morris method is recommended.

Quadratic Combination for a smooth model can be used to assess a consumption threshold thanks to the estimation of the mean and standard deviation. However, it does not provide the overall

distribution. If the total distribution is desired to set the threshold, then, Latin Hypercube is preferred to the standard Monte Carlo method since it enables us to cover the input space and the convergence is fast.

Several methods are also compared to assess the probability of exceeding a threshold: FORM/SORM, Monte Carlo, Latin Hypercube, Quasi-Monte Carlo, directional Sampling and importance Sampling (coupled to FORM). FORM method assesses very quickly (13 times faster than the second fastest method in this case) the failure probability with an acceptable relative error (less than 30% for a probability less than 5%). As in a building, exceeding the threshold does not present a major risk to 0.1% so that margin of error can be accepted. However, FORM/SORM do not calculate the confidence interval for the results. In this case, Importance Sampling coupled with FORM provides a good compromise between computing time and accuracy of results.

Lastly, two metamodel families were compared: Kriging and Sparse Polynomial Chaos expansion. We failed to build a Kriging metamodel without a high relative error caused by a problem of overfitting. However, Sparse Polynomial Chaos led to an excellent approximation of the model in a few simulations (200 simulations for 24 parameters) and obtained, in a short time, Sobol indices. A method to build a sparse polynomial chaos has been suggested. Fig. 14 shows the selected methods.

Finally, a process of selection of the statistics method is proposed:

- First, the number of parameters is reduced with:
 - The **Quadratic Combination** method if the model is regular enough
 - The **Morris** method, otherwise
- If the model is smooth enough and runs in more than a minute the construction of a metamodel using **Sparse Polynomial Chaos** method is recommended.
- When a model is too bumpy (not smooth) to be expanded in a Sparse Polynomial basis, we suggest using **FORM** method to assess a threshold exceedance probability and sensitivity in the

neighborhood of the threshold. This method is useful to check the risk of exceeding an existing threshold and can be used in the case of a massive retrofit or the accordance of an energy performance label. If the threshold has to be set from scratch, this method can be used iteratively to determine the probability of several thresholds and stop when the desired risk is reached.

- Finally, when a model has more than 4 discrete parameters or outputs, sampling methods are suggested since their disadvantage of high computational time is no longer comparable to the other methods. In this case,
 - **Latin Hypercube** sampling provides the probability density of the outputs
 - **FORM coupled to Importance Sampling** provides the probability of threshold exceedance and the confidence interval

24 parameters have been selected, instead of the 9 main parameters, to test the robustness and accuracy of the probability algorithm with more than 20 parameters. Even if most of the tested methods' computational times are not directly linked to the number of parameters, adding 15 extra-parameters unnecessarily complicated the study: the time required to set the extra parameters provides a slight improvement in the accuracy of the result.

Total annual electricity consumption is the only parameter being considered and tracked in this study. In other cases, other key performance indicators can be considered as part of the energy performance contracting process to ensure maximum value to customers and building owners, such as heating or cooling consumption. Moreover, when the electricity consumption is subdivided into the various uses, these methods also allow us to study the various end uses of electricity within the building and identifying specific parameters to enhance the performance of the building.

Previous recommendations can be applied to any building, depending on the model regularity, the number of parameters and the goal of the studies, as these methods fit thermal simulation. For instance, This method has already been applied at ENGIE-Axima to several buildings (swimming pools, educational buildings) to determine the key parameters and the consumption threshold to create the EPC.

Acknowledgment

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ANNEX 1. building thermal zoning





ANNEX 2. Selected inputs

Name	Description	Distribution	Category
AlphaAHU1Sup	Aggregated parameter of the supply fan of AHU 1 [-]	Kernel smoothed distribution obtained by carrying an upstream uncertainty analysis performed on the supply fan parameters [38]	AHUs
AlphaAHU1Ex	Aggregated parameter of the recovery fan of AHU 1 [-]	Kernel smoothed distribution obtained by carrying an upstream uncertainty analysis performed on the recovery fan parameters [38]	AHUs
AHU1SupDistCoef	AHU 1 supply airflow distribution coefficient [-]	Truncated Normal (0, 0.067, -0.27, 0.27)	AHUs
AHU1ExDistCoef	AHU 1 recovery airflow distribution coefficient [-]	Truncated Normal (0, 0.067, -0.27, 0.27)	AHUs
AHU1Leak	AHU 1 leak flow [%]	Truncated Normal (0.1, 0.03, 0, 0.23)	AHUs
AHU1RecupEff	AHU1 recuperator efficiency [-]	Beta (0.75, 0.03, 0.65, 0.8)	AHUs
AlphaAHU2Sup	Aggregated parameter of the supply fan of AHU2 [-]	Kernel smoothed distribution obtained by carrying an upstream uncertainty analysis performed on the supply fan parameters [38]	AHUs
AlphaAHU2Ex	Aggregated parameter of the recovery fan of AHU2 [-]	Kernel smoothed distribution obtained by carrying an upstream uncertainty analysis performed on the supply fan parameters [38]	AHUs
AHU2DistCoef	AHU 2 airflow distribution parameter [-]	Truncated Normal (0, 0.067, -0.27, 0.27)	AHUs
AHU2Leak	AHU 2 leak flow [-]	Truncated Normal (0.1, 0.03, 0, 0.23)	AHUs
AHU2FreshAir	AHU 2 Fresh air rate [-]	Truncated Normal (100, 6, 76, 124)	AHUs
NomNorthHPEER	Nominal North Heat pump EER [-]	Beta (2.83, 0.14, 2, 3)	Heat Pumps
AuxNorthHP	Electric power percentage of auxiliaries in cold and hot modes North HP [-]	Beta (1.25, 0.45, 0, 2)	Heat Pumps
SlopesNorthHP	Multiplier of the slopes of North HP matrix performance [-]	Beta (1, 0.05, 0.8, 1.1)	Heat Pumps
InterceptsNorthHP	Multiplier of the intercepts of North HP matrix performance [-]	Beta (1, 0.05, 0.8, 1.1)	Heat Pumps
NomSouthHPEER	Nominal South Heat Pump EER [-]	Beta (3.46, 0.1, 2.7, 3.6)	Heat Pumps
AuxSouthHP	Electric power percentage of auxiliaries in cold and hot modes South HP [-]	Beta (1.25, 0.45, 0, 2)	Heat Pumps
SlopesSouthHP	Multiplier of the slopes of South HP matrix performance [-]	Beta (1, 0.05, 0.8, 1.1)	Heat Pumps
InterceptsSouthHP	Multiplier of the intercept of South HP matrix performance [-]	Beta (1, 0.05, 0.8, 1.1)	Heat Pumps
NorthHPkL	Overall North HP network loss coefficient [kW/K]	Truncated Normal (0.024, 0.004, 0.008, 0.04)	Water Networks
PumpEffNorthHP	Pump efficiency of north HP network [-]	Beta (0.44, 0.016, 0.34, 0.46)	Water Networks
UnderfloorkL	Overall underfloor heating system network loss coefficient [kW/K]	Truncated Normal (0.018, 0.003, 0.006, 0.03)	Water Networks
PumpEffUnderfloor	Pump efficiency of underfloor heating system network [-]	Beta (0.17, 0.02, 0.1, 0.2)	Water Networks
ColdUnderfloorInTemp	Cold underfloor heating system network input temperature [°C]	Truncated Normal (17, 0.34, 15.67, 18.3)	Water Networks
HotUnderfloorInTemp	Hot underfloor heating system network input temperature [°C]	Truncated Normal (30, 0.3, 28.7, 31.3)	Water Networks
AHUkL	Overall AHU network losses coefficient [kW/K]	Truncated Normal (0.004, 0.0007, 0.0013, 0.007)	Water Networks
PumpEffAHU	Pump efficiency of AHU network [-]	Beta (0.51, 0.015, 0.45, 0.53)	Water Networks
NorthBeamkL	Overall north chilled beam network loss coefficient [kW/K]	Truncated Normal (0.038, 0.006, 0.013, 0.06)	Water Networks
PumpEffBeam	Pump efficiency of north chilled beam network [-]	Beta (0.43, 0.015, 0.33, 0.45)	Water Networks
ColdBeamInTemp	Cold north chilled beam network input temperature [°C]	Truncated Normal (17, 0.3, 15.7, 18.3)	Water Networks
HotBeamInTemp	Hot north chilled beam network input temperature [°C]	Truncated Normal (40, 0.3, 38.7, 41.3)	Water Networks
SouthHPkLHA	Overall South HP network loss coefficient in heated area [kW/K]	Truncated Normal (0.024, 0.004, 0.008, 0.04)	Water Networks
SouthHPkLUA	Overall South HP network loss coefficient in unheated area [kW/K]	Truncated Normal (0.029, 0.00483, 0.009, 0.048)	Water Networks
PumpEffSouthHP	Pump efficiency of South HP network [-]	Beta (0.46, 0.016, 0.36, 0.48)	Water Networks
SouthHPInTemp	South HP input temperature [°C]	Truncated Normal (17, 0.3, 15.7, 18.3)	Water Networks
UBuilding	Building heat loss coefficient [-]	Truncated Normal (1.1, 0.03, 1, 1.2)	Building walls
Capacitance	Total thermal capacitance of zones air plus that of any mass not considered as walls (e.g. furniture.) [kJ/K]	Truncated Normal (500, 125, 0, 1000)	Building walls
WSolarGain	Window solar gain [-]	Truncated Normal (0.39, 0.026, 0.286, 0.494)	Building glazing
UWindow	Window Heat transfer coefficient(Uw) [-]	Truncated Normal (1, 0.03, 0.8, 1.13)	Building glazing
AirTightness	Air tightness of the building [m ³ /h/m ²]	Beta (1.7, 0.13, 1.5, 2.2)	Infiltrations
SoilTempCoef	Soil temperature coefficient[-]	Truncated Normal (1, 0.067, 0.73, 1.27)	Ground exchanges
CoolSetTemp	General cooling set point temperature [°C]	Uniform(25, 27)	Set Points
HotSetTemp	General heating set point temperature [°C]	Uniform(18, 22)	Set Points
AHU1BlowTemp	AHU 1 Blowing setting temperature [°C]	Uniform(15, 17)	Set Points
ChillNorthHPInTemp	Chilling mode North HP input temperature [°C]	Uniform(6, 8)	Set Points
HeatNorthHPInTemp	Heating mode North HP input temperature [°C]	Uniform(39, 41)	Set Points
NomUsersNumber	Nominal user number multiplier [-]	Uniform(0.8, 1.2)	Occupancy
LightPower	Lighting power multiplier [-]	Uniform(0.9, 1.1)	Lighting
EquipPower	Equipment power multiplier [-]	Uniform(0.9, 1.1)	Equipment

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