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Framework for effective robust design of building energy systems: Bridging the gap between predicted and actual energy use

Jan Kocbach[1*], Kjetil Folgerø[1], Astrid Marie Skålvik[1], Maria Olsen Wulff [2], Bianca Kjellberg[2], Trond Thorgeir Harsem[2]
[1] NORCE Norwegian Research Centre, Bergen, Norway
[2] Norconsult AS, Sandvika, Norway
* *corresponding author: Jan.Kocbach@norceresearch.no*

Abstract

Practitioners working on building performance simulations do seldom apply uncertainty and sensitivity analysis using state-of-the-art global methods in their daily workflow. With stricter building regulations imposed year by year, a corresponding change in workflow has been identified as one important way to bridge the increasing gap between predicted and actual energy use. This study describes how statistical methods from research can be adapted to an efficient workflow in a practical setting, concretised through description of a proposed framework and methodology, and application on a case study for a hospital in Northern Norway.

Introduction

There is often a significant gap between predicted energy performance of buildings and energy use once buildings are operational (de Wilde 2014). Bridging this gap is crucial for the industry to deliver buildings that are robust towards change and uncertainties in design parameters. However, as building regulations have become stricter, the difference has increased (de Wilde 2014). One explanation for the increasing performance gap is that stricter regulations requires tuning of a large number of input parameters in building energy simulations to achieve highly optimized solutions. Combining a large number of optimistic "best case" input settings in a single-point optimized solution will, however, lead to designs that may be very sensitive to changes in input parameters. We suggest that one way to bridge the increasing performance gap is to give practitioners access to tools for robust design of building energy systems.

The aim of this research is therefore to develop a framework and methodology that makes it feasible for practitioners working on building performance simulations (BPS) to readily apply state-of-the-art uncertainty and sensitivity analysis in their daily workflow.

Uncertainty analysis and sensitivity analysis

Uncertainty analysis in building energy assessment has become an active research field as a number of factors influencing energy use in buildings are inherently uncertain (Tian et al. 2018). Monte Carlo-based simulation is the most widely used uncertainty propagation method in building energy assessment, although non-sampling methods are also in use (Tian et al. 2018, Pang et al. 2020).

Sensitivity analysis is often used in conjunction with uncertainty analysis to quantify the contributions of input parameters to the uncertainty in the model output (Tian 2013, Saltelli et al. 2019). Sensitivity analysis methods can be grouped into local (LSA) and global sensitivity analysis (GSA) methods (Saltelli et al. 2008). LSA methods are computationally inexpensive, but examine only a limited part of the problem space. Dynamic simulation models for BPS are typically non-linear (Pang et al. 2020), and LSA approaches are therefore not robust because results are strongly dependent on the values chosen for the nominal case, potentially giving highly misguiding results (Saltelli et al 2019).

There are a wide range of GSA methods available, with varying computational cost, robustness and accuracy (Saltelli et al. 2008, Pang et al. 2020, Tian et al. 2018). For studies with a high number of input parameters and high computational cost for each model evaluation, as typical is the case in BPS, accurate calculation of the importance of all input parameter in a global sense is very computationally costly. For such cases, a recommended approach is to first reduce the number of input parameters using a global screening method [e.g. Morris elementary effects method (Morris 1991), requiring a sampling size of around 10 times the number of input parameters], before proceeding with a reduced number of input parameters found to influence the output parameters of interest (Saltelli et al. 2008, Tian et al. 2018, Pang et al. 2020). Regression methods have been among the most widely used GSA methods for sensitivity analysis in building energy analysis (Tian 2013); these methods are easy to understand and relatively fast to compute, requiring a sample size around 10 – 100 times the number of input parameters (Pang et al. 2020). Many regressions-based indicators for the importance of input parameters can then be applied, such as e.g. standardised regression coefficients (SRC) which has been widely used in BPS (Tian 2013, Pang et al. 2020). SRC is however only applicable for uncorrelated input parameters, and care must be taken for non-linear models as its calculation is based on multiple linear regression (Tian 2013).

For highly non-linear models, Sobol's variance-based sensitivity indices have been shown to be effective in identifying the individual, interaction and total effects of model input parameters, although at a high computational cost [typically 500 – 1000 times the number of input parameters (Saltelli et al. 2008)]. Monte Carlo filtering is a GSA-based approach which has lower computational cost, but which is nevertheless applicable for non-linear models (Saltelli et al. 2008, Østergård et al. 2017); this approach helps identifying regions of the input space that meet certain criteria. Use of meta-models is a machine learning based approach to reduce the computational cost for GSA of non-linear models that has been given a lot of attention for building performance analysis the last years (Van Gelder 2014b, Østergård et al. 2018).

Input and output parameters

The basis for any uncertainty or sensitivity analysis in BPS involves (i) determining input parameters that may influence the building performance, (ii) specifying the probabilistic distributions and possible correlations for all uncertain input parameters and (iii) selecting which output parameters of the model to analyse. The main approaches are summarized in recent reviews (Tian et al. 2018, Pang et al. 2020), where sources of uncertainty in building performance analysis are classified into different areas and each area is discussed in detail.

The relative importance of input parameters varies greatly from study to study based on the characteristics of the case and the output parameters of interest (Tian et al. 2018, Pang et al. 2020). Thus, generally one cannot know *a priori* which input parameters will have negligible impact, and thus a large enough range of input parameters should be included in the initial stages of BPS. A good approach is to do a pre-analysis step using provisional probabilistic distributions to identify the most influencing parameters, and then update the provisional distributions of the most influencing parameters based on the resulting sensitivity ranking (Van Gelder et al. (2014).

Most of the existing case studies have done sampling by treating input parameters as independent parameters (Pang et al. 2020, Tian et al. 2018). However, neglecting correlation between input parameters may lead to highly inaccurate results as exemplified in Pang et al. (2020).

Sensitivity and uncertainty analysis in daily workflow

A systematic, global approach for uncertainty and sensitivity analysis is not regularly used by practitioners in charge of building energy simulations, especially in the Nordic countries (Østergård et al. 2020), partly due to availability of tools and methodology tailored to the typical workflow of practitioners. This is in strong contrast to the recommendations for best practise in sensitivity analysis given in Saltelli et al. (2019), where global exploration of the space of input factors is recommended.

Some developers of BPS software have integrated global sensitivity and uncertainty analysis options in their software, e.g., the latest version 5.0 of IDA Indoor Climate and Energy (EQUA Simulation AB, Stockholm, Sweden). However, practitioners nevertheless often perform uncertainty and sensitivity analysis manually and locally using One-parameter-at-a-time (OAT) type LSA approaches, and typically only for a few parameters that are important based on the practitioners' previous experience. Specifically for the Norwegian market, the leading tool for energy simulations of buildings, Simien (Simenergi, Lysaker, Norway), offers no built-in or add-on functionality for sensitivity or uncertainty analysis.

There are very few published studies on design methodology for decision making for building performance design from a more overall perspective, i.e., how to enable a good workflow for decision making application of sensitivity and uncertainty analysis for researchers or practitioners. One early work in this direction was Van Gelder et al. (2014) who proposed a multi-step probabilistic analysis methodology, including screening, and a multi-layered sampling scheme.

This topic is also addressed in a review article on BPS supporting decision making in early design (Østergård et al. 2016), where it was found that few of the existing solutions allow the designer to handle uncertainties and to explore large design spaces, while also lacking the ability to guide the designer towards better performing buildings. Østergård has later published several studies focused on holistic design methodology for decision-making, with applicability for both researchers and practitioners. These studies range from informed decision-making in early building design (Østergård et al. 2017) to presenting a framework for informed BPS (Østergård et al. 2020).

In this study, a framework and methodology for uncertainty and sensitivity analysis in BPS is presented. The framework has been developed with focus on applicability in a daily workflow of practitioners, combining state-of-the-art methods described in the preceding sections with ease-of-use. A case study is included to illustrate how this methodology can be applied to understand and improve a hospital's energy performance, potentially closing the big gap observed between calculated and measured energy consumption for this building.

Methods

SensiRob framework

The SensiRob framework is a Python-based framework that interfaces with building energy simulation software through Extensible Markup Language (XML) files. An executable version is available for use by practitioners. The framework currently interfaces with the leading tool for energy simulations in buildings in Norway, Simien, but is built with a general structure to allow integration with other BPS tools. Simien is based on the methodology described in the Norwegian standard NS3031:2014, which compiles with the European standard EN ISO 13790:2008. SensiRob can run up to 20 Simien simulations in parallel, allowing for more than 5.000 annual, hourly Simien-simulations within an hour on a regular desktop computer. A standardized Excel-format is defined for setting up parameter variations, and a graphical user interface (GUI) is used for performing analysis and postprocessing. The framework also includes a sandbox for testing of algorithms and concepts for research, e.g. comparing the performance of different meta-models and sensitivity analysis methods.

The statistical methods in the SensiRob framework are built around open source packages for parameter sampling, uncertainty analysis, GSA and meta-modelling, including the Python-packages PyDoe, SALib, statsmodels, scipy.stats and scikit-learn.

Input and output parameters

Following Tian et al. (2018), the input parameters are divided into four main categories; weather data, building envelope, HVAC system, and occupant behaviour. In addition, an additional category from Pang et al. (2020), "Control system", is added. Some input parameters may be defined to be in more than one category.

Input parameters are defined in an Excel-sheet which can be reused across projects. Following Van Gelder et al. (2014), input parameters are defined as uncertainty parameters (e.g. workmanship and occupant behaviour), design parameters (controllable by the designer or potential errors) or both. For each uncertainty parameter, the probabilistic distributions are defined by choosing distribution (e.g. normal distribution, left-tailed normal distribution, uniform distribution) and the input range. For each design parameter, distinct design values are given (either as a relative change or absolute value).

Simien, Energy Plus and many other BPS divide the studied buildings into thermal zones. A thermal zone is an air volume at uniform temperature, plus all the heat transfer and heat storage surfaces bounding or inside of that air volume. A typical building can have up to 10-15 zones, and input parameters like e.g. set-temperatures for heating and cooling and U-values for the walls and windows are generally set separately for each zone. In SensiRob, probabilistic distributions can be set either globally with the same variation in all zones (100% correlation), separately for each zone (no correlation), separately for a selection of zones (100% correlation within some zones, no correlation with other zones) or by setting a specific correlation (e.g. 75%) between a parameter in all zones. Most published case studies typically use 100% correlation (grouped parameters) or no correlation (Pang et al. 2020), which will often give a too strong or too weak effect of a parameter change, respectively. The disadvantage of using correlation settings other than 100% is that the number of input parameters increases significantly. In addition to allowing correlations between input parameters that occur in different zones, correlations between different parameters within or across zones can also be set.

Simien offers a large range of output parameters, including annual/peak building electricity consumption, annual energy usage for heating/cooling/ventilation, overheating hours. All analysis options can be performed for any of these output parameters, and re-evaluation for other parameters can be done without re-simulation.

Statistical methods in SensiRob

The SensiRob framework integrates a wide range of sampling techniques and statistical methods for uncertainty and sensitivity analysis. The Morris elementary effects method is implemented to identify input parameters of high importance, using the scheme of Ruano et al. (2012) to identify optimal trajectories. The main component of the framework is a quasi Monte Carlo (qMC)/Latin hypercube sampling (LHS) based uncertainty and sensitivity analysis, where sampling can be done using either LHS or Sobol sequences. To determine the number of sampling points required for the analysis, convergence tests can be performed. Regression methods, have been implemented as global methods for determining the importance of input parameters, including SRC, dominance analysis based of R^2 change and Random Forest based importance measures generally applicable for non-linear models (Antoniadis et al. 2021). Further, Monte Carlo filtering is implemented using the Kolmogorov-Smirnov test, accompanying visualization of input parameter distributions corresponding to a specified part of a given output parameter.

Variance-based Sobol indices are also implemented, but due to the high computational demand these are currently not part of the workflow. Several metamodels are implemented in the research sandbox, including Multivariate adaptive regression splines (MARS) and Gaussian processes (GPR) which were recommended in two different comparisons of meta-modelling techniques for BPS (Østergård et al. 2018, Van Gelder 2014b).

Design parameter analyses are added as another layer in SensiRob. For a quick overview of the different designs a One-design-at-a-time (ODT) analysis is possible, but this is not recommended as a stand-alone analysis as uncertainties are neglected. Functionality for performing a full uncertainty analysis for each design (ODT-MC) is included to investigate how each design is influenced by the uncertainty in the input parameters. Further, methodology to investigate the influence of changing several design parameters simultaneously is provided, optionally with restraints on how many design parameters can be changed (e.g. maximum of two changes), enabling a robust design process. Finally, it is possible to do a full uncertainty and sensitivity analysis where the parameter range of the GSA is expanded to also include the span of the design parameters, to get deeper insight into the importance of the design parameters in a global setting.

Workflow

The workflow the user is led through in the SensiRob framework is closely linked to the process proposed by Van Gelder et al. (2014), and also has similarities to the process described in Østergård et al. (2020), giving the following multi-step process:

(i) **Parameter identification.** Identify and evaluate uncertainty and design parameters, including a preliminary (broad) range of possible values for each parameter. Input parameters are defined in an Excel-sheet which can be reused across projects, providing a good starting point based on previous experience.

(ii) **Screening.** Perform a Morris or qMC/LHS analysis (depending on the number of input parameters) where all parameters are grouped (100% correlated across zones) to determine which parameters can be neglected in further analysis, for which parameters an accurate probabilistic distribution must be given and where correlation should be considered. Screening can be done for several output parameters. Parameters can be automatically removed based on rank or value of importance.

(iii) **Uncertainty and sensitivity analysis.** With updated parameter values and correlation considerations, perform a qMC/LHS analysis to find an estimate for the uncertainty in the output parameters of interest, and evaluate the relative importance of the input parameters using regression-based methods or Monte Carlo filtering.

(iv) **Design analysis.** For each design, perform a qMC/LHS analysis to investigate the influence of the design parameters under uncertainty. Based on the aim of the analysis, various analyses with combinations of design parameters can also be made.

Based on this workflow, the practitioner will gain valuable insight into the model compared to today's approach were selected input parameters are changed manually one at a time. Currently, the SensiRob framework is in the internal testing phase, and the workflow is expected to be refined when additional experience from practical applications becomes available.

Results

The application of the SensiRob framework and methodology in a practitioner's workflow is demonstrated using a case study for a hospital building in Northern Norway. Here both a Simien simulation model and selected measurement and experience data is available. For this building, the actual energy usage when put in operation was significantly higher than projected, and thus this is an interesting case study.

The Simien model of the hospital consists of 13 thermal zones. Compared to the original model, heat pump and chiller is excluded from the model (coefficient of performance set to 1) and the heating and chilling capacity is set so high that temperature requirements are always fulfilled. This was done to simplify the interpretation of the results when using a single output parameter in the presented results. The output parameter considered in the presented analysis is the HVAC (Heating, Ventilation and Air Conditioning) energy usage.

The results presented in this section follow the steps in the SensiRob framework, as described under Methods.

Step 1: Parameter identification

Input parameters along with nominal value and probabilistic distributions considered in the analysis are shown in Table 1; 27 uncertainty parameters across 13 zones, a total of 273 individual parameters. To address the errors that could be made in the design or building phase in the SensiRob framework, a set of design parameter variations (12) are defined to represent possible errors in the design or building phase. Uncertainty parameters are given with 95% confidence interval and truncated normal distributions are used for all uncertainty parameters.

Step 2: Screening

A Morris screening analysis with 10 optimal trajectories and 4 levels is performed in accordance with recommendations by Saltelli et al. (2004), with input parameters grouped (100% correlated across groups; 260 simulations for 27 grouped parameters). Results of the Morris screening analysis are shown in Figure 1, where the points represent the absolute value of the mean elementary effect μ* (x-axis) and the standard deviation of the elementary effect σ (y-axis) for each parameter. According to a classification scheme proposed by Sanchez et al. (2014), the ratio σ/μ* allows the characterisation of the model parameters in terms of linearity and monotony. Parameters with σ/μ* larger than 1.0 can be classified as non-linear and/or non-monotonic (three parameters; equipment power, ventilation supply temperature summer and ventilation air volume) and parameters with σ/μ* smaller than 0.1 can be classified as linear (three parameters; ventilation exchanger efficiency, winter temperature and specific fan power).

Based on this screening analysis, additional effort was used to accurately update the probabilistic distributions for parameters with high values for μ* or σ. In this case, probabilistic distributions for all parameters which are named in Figure 1 (13) were considered, to ensure that they are as accurate as possible. Analysis with higher number of trajectories (up to 30) and levels (up to 10) gave similar results with no additional parameters introduced into the 12 highest ranked parameters.

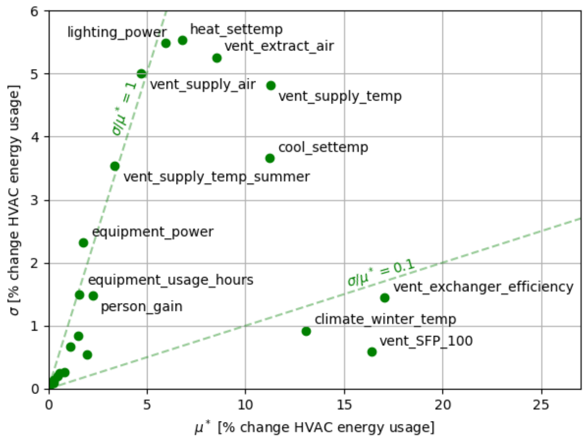

Figure 1. Results from Morris screening analysis using 10 trajectories, showing the standard deviation versus the absolute value of the mean elementary effect for each input parameter. Parameters of high importance are named. Parameters left of the dashed σ/μ=1 line are classified as non-linear/non-monotonic and parameters right of the σ/μ*=0.1 line are classified as linear.*

Table 1. Parameter values for the hospital case study. Where nominal values vary across thermal zones, a range is given. Bounds are absolute minimum and maximum values where the distribution is truncated. The design changes column defines the design parameters input to the SensiRob framework, each corresponding to potential issues. Where a parameter belongs to multiple categories, additional categories are indicated by their first letter.

Category	Parameter	Unit	Nominal values	Bounds	Uncertainty (95% conf.)	Design changes
HVAC - Ventilation	Vent Supply Air	m^3/hm^2	12 – 50	0 – 80	5 %	+ 20%
HVAC - Ventilation	Vent Extract Air	m^3/hm^2	12 – 50	0 – 80	5 %	+ 20%
HVAC - Ventilation	Vent Supply Temp	°C	19 – 21	15 – 23	2	+ 2
HVAC - Ventilation	Vent Supply Temp Summer	°C	19	15 – 23	2	- 3
HVAC - Ventilation	Vent SFP 100	$kW/m^3/s$	1.5	0.1 – 10	50 %	
HVAC - Ventilation	Vent Exchanger Efficiency	%	80	0 – 100	10 %	- 5 %%
HVAC - Ventilation	Vent Heat Coil Capacity	W/m^2	100	0 – 200	20%	
HVAC – Cooling + U + C	Cool Settemp	°C	24	23 – 30	3	- 1
HVAC – Heating + U + C	Heat Settemp	°C	21	12 – 23	3	+ 2
HVAC – Heating + U + C	Heat Settemp Night	°C	19	12 – 23	4	+ 2
User behaviour	Num Persons	-	6 – 102	0 – 200	50 %	
Control system + U	Lighting Power	W/m^2	8 – 60	0 – 100	50 %	
Control system + U	Lighting Power Holiday	W/m^2	0	0 – 100	10	
Control system + U	Lighting Usage Hours	h (/day)	12.75 – 24	0 – 24	2	
Control system + U	Equipment Power	W/m^2	6.7 – 65.5	0 – 100	20 %	
Control system + U	Equipment Power Holiday	W/m^2	0	0 – 100	2	
Control system + U	Equipment Usage Hours	h (/day)	9.9 – 22	0 – 24	2	
Weather	Summer Temp	°C	8.9	-20 - 20	3	
Weather	Winter Temp	°C	-4.2	-20 - 20	3	
Building Envelope	Uval Façade	W/m^2K	0.12–0.18	0.05 – 1	0.02	+ 0.1
Building Envelope	Uval Separator Wall	W/m^2K	0.25	0.05 – 1	0.02	
Building Envelope	Uval Roof	W/m^2K	0.1	0.05 – 1	0.02	+ 0.08
Building Envelope	Uval Window	W/m^2K	0.8	0.05 - 2.5	0.02	+ 0.4
Building Envelope	Uval CoolPipes	W/m^2K	0.2	0.05 – 1	0.02	
Building Envelope	Infiltration N50	h^{-1}	0.6	0 – 7	0.2	+ 1.9
Building Envelope	Thermal Bridge Norm	$W/K/m^2$	0.03	0 – 1	50 %	+ 300 %
Building Envelope	Window Solar Fact	-	0.51	0 – 1	30 %	

Step 3: Uncertainty and sensitivity analysis

The high computational cost due to application of Monte Carlo uncertainty simulation can be reduced by using more efficient sampling methods, such as, e.g., LHS or Sobol sequences (Kucherenko et al. 2015). The general recommendation for a LHS sample size is stated as ten times the number of variables according to Tian et al. (2018) and Loeppky et al. (2009), while Pang et al. (2020) recommends using 10 – 1000 times the number of variables depending on analysis method. The SensiRob framework gives the possibility to study convergence by incremental sampling (Pang et al. 2020). Here this was done by calculating selected output parameter and SRCs for 6 different sample sizes (64 to 2048 samples) repeatedly (5 times per sample size), and studying convergence properties. For the full set of 27 parameters grouped (100% correlation across zones), 512 samples were required for stable output parameter and SRC for the 10 input parameters with highest SRC. For the 27 parameters individually (no correlation across zones), acceptable stability for the output parameter was found for 512 samples, while 2048 samples were necessary for SRC. For Monte Carlo filtering a higher number of samples give better results, and thus 4096 samples has been used across all analyses for the current case.

The uncertainty analysis for change in HVAC energy usage due to the input parameter variations given in Table 1 is presented in Figure 2 for varying correlation across zones. The mean change in HVAC energy usage is found to be 18% across all correlation settings, with uncertainty (95% confidence interval) ranging from 38% (100% correlation between zones) to 18% (no correlation).

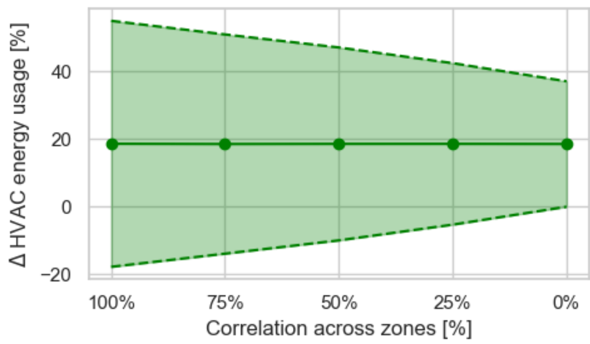

Figure 2. Change in HVAC energy due to variation of input parameters (thick line, circles) for varying correlation across zones. Uncertainty (95% conf. int.) shown using shaded area.

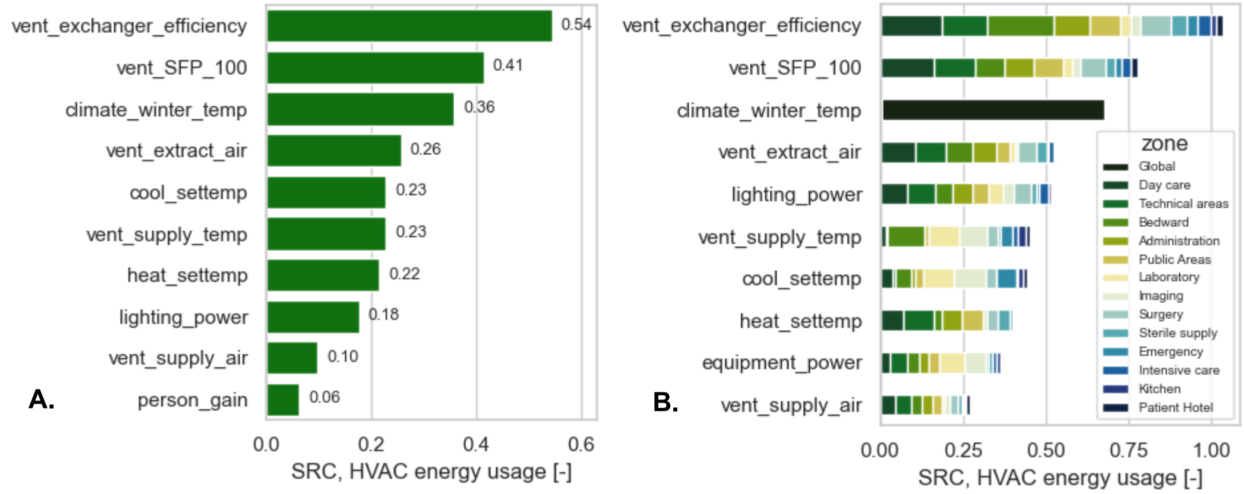

Figure 3. Relative importance of input parameters for HVAC energy usage based on SRC for (A) the case with full correlation across zones (R^2=0.85), and (B) the case with no correlation across zones (R^2=0.89). The 10 input parameters with highest importance are shown to illustrate the application of the framework. In (B), SRC values are shown across zones using a stacked bar plot, where each zone is shown using a separate colour.

Next, a sensitivity analysis is made to analyse the relative importance of the input parameters. In Figure 3, the relative importance of input parameters is shown using the SRC. For the case with full correlation across zones in Figure 3 (a), parameters related to ventilation [exchanger efficiency and SFP (Specific Fan Power)] are found to be of highest importance, ahead of a weather parameter (winter temperature). Other important parameters are related to cooling and heating set temperature and lighting power. In Figure 3 (b), corresponding data for the case with no correlation across zones is presented. The order of importance is the same for the four most important parameters when summating the contribution from individual zones. However, large differences in importance across zones can be observed.

Figure 4 shows which input parameter values (normalized) lead to low HVAC energy usage (green) and high HVAC energy usage (red) for the 100% correlation case. This is found by identifying the 10% of the 4096 simulations which gives lowest and highest HVAC energy usage, respectively, and plotting the distribution. Monte Carlo filtering is done by comparing the full distribution of each input parameter with the selection in a two-sample Kolmogorov-Smirnov test. P-values below 0.01 indicate that the parameter is of critical importance for the investigated criterium, p-value between 0.01 and 0.1 indicate that the parameter is important and above 0.1 indicates that the parameter is insignificant (Saltelli et al. 2004).

While SRC is useful to understand the importance of the input parameters, potential non-linearities in the model means that some input parameters may have high SRC while only being important for either positive or negative changes in HVAC energy usage. Monte Carlo filtering is an approach that helps identifying regions of the input space that meet certain criteria, applicable for non-linear analysis and correlated input, giving excellent analysis and visualization possibilities. A combination of Monte Carlo filtering with interactive visualization is a method which can be intuitively understood by practitioners, as also Østergård et al. (2020) has explored.

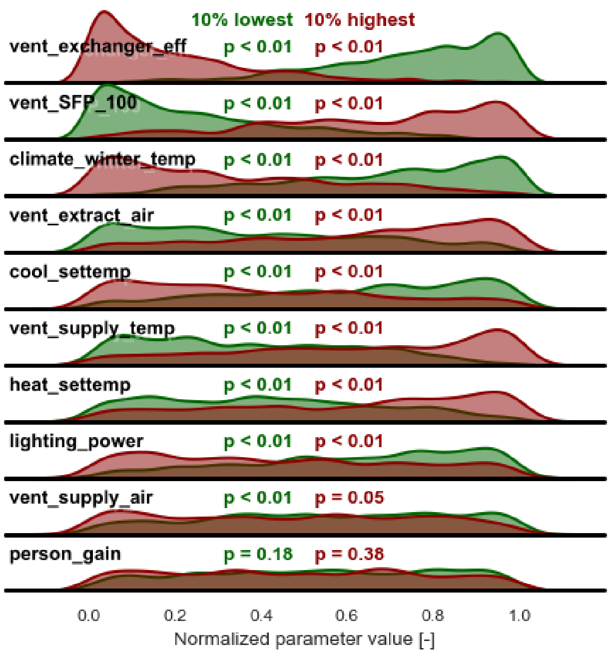

Figure 4. Monte Carlo filtering visualized for case with full correlation across zones. Distribution of input parameters (normalized) corresponding to the 10% lowest/highest HVAC energy usage is shown in green/red along with corresponding p-value for the two-sample Kolmogorov-Smirnov test.

Step 4: Design analysis

The aim of the design analysis in the current case study was to understand how different issues that could occur in the design phase, building phase or operational phase would influence the HVAC energy usage. One such issue could be that the infiltration-value for the building envelope in the finished building is significantly higher than planned for, either due to setting a too optimistic estimate in the design phase or due to poor follow-up in the building phase. Another issue could be that the ventilation supply temperature was set to 19°C in summer, but in reality turned out to be set to 16°C. Twelve such potential issues have been identified and are listed in Table 1 in the column "Design changes".

A typical approach for a practitioner without specific software for global uncertainty and sensitivity analysis available, would be to perform a one-design-at-a-time (ODT) analysis, i.e., consider the isolated effect of each issue, and based on this analysis consider if the increase in HVAC energy usage is acceptable. With this approach, the combined effect of uncertainties considered in step 3 and the considered issue would not be found. Also, the combined effect of several issues would be overlooked.

In Figure 5, results from an ODT analysis for each of the 12 issues is shown using dark green bars. In the same figure, the design change corresponding to each issue is combined with an uncertainty analysis, using the probabilistic distributions for input parameters from step 3. The case with 75% correlation across zones is considered, all 27 parameters are included, and 512 LHS samples are used for each design. The issues are sorted by highest combined effect. It can clearly be seen that the combined uncertainty is influenced by non-linear effects, as the importance order based on the ODT alone is different. Investigation of the combined effect of multiple design changes with uncertainty is also facilitated in SensiRob, but is not included in this case study.

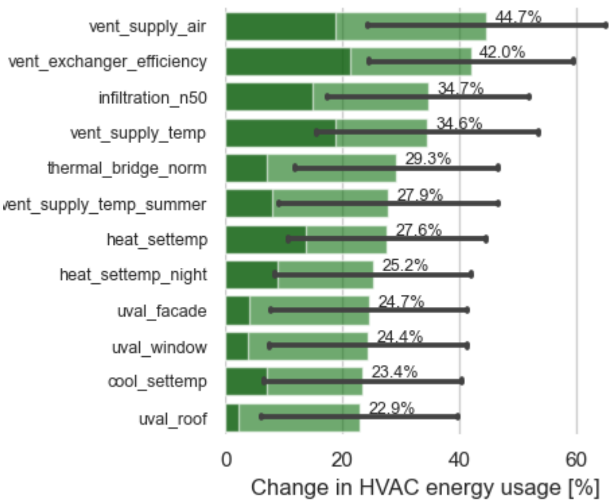

Figure 5. Dark green bars: ODT analysis of change in HVAC energy usage for each design change (issue). Light green bars: Combined effect of design change and uncertainty. Error bars show one standard deviation.

Discussion

In this study we have shown how the SensiRob framework and methodology can be implemented in a practitioner's workflow by considering a case study for a hospital building in Northern Norway. For a consultant already using a supported tool for BPS, the availability of such a framework with accompanying methodology is a necessary first step to enable the use of global uncertainty and sensitivity analysis among practitioners.

In order to integrate the use of this type of frameworks and methodologies in the daily workflow of practitioners working on BPS beyond the pilot phase, high focus must be put on leading the user through a process that can be repeated and automatically documented for each new project. The 4-step process demonstrated in the case study has many of the characteristics that are required in order to succeed; automatic import of existing simulation files, re-usable Excel-sheet with probabilistic distribution for potential input parameters that can be reused across projects, the possibility to make many simulations in a short time-span and intuitive visualizations. The framework will be further developed in cooperation with practitioners in an ongoing project.

For the considered case study, analysis of measurements after the hospital had been in operation for one year showed a 20% higher energy usage for heating and a 22% higher energy usage for ventilation than projected. According to De Wilde (2014), the main reason for the performance gap between predicted and measured energy usage is often a different occupant behaviour than assumed in the design stage. This was found to partly the reason also in our case; in many rooms the set-temperature for heating was manually set to 23°C, while it was set to 21°C in the control system and in the design.

Another typical issue pointed out by De Wilde (2014) is that the quality of the building is often not in accordance with specification, with insufficient attention to both insulation and airtightness. This was also found in the considered case study; both infiltration rate and thermal bridges were not according to plans and BPS input parameters due to lack of control in the building phase. Thermal imaging showed leakage around doors and windows, and thermal bridges with higher heat conductivity than projected were found. The higher energy usage for ventilation was found to be due to the use of higher temperature than projected for the ventilation at night. This was an indirect cause of the poor building performance, which required a change of control system settings to assure required daytime temperatures.

Comparing with the current case study results, the ventilation system was generally identified as the most critical component, with several ventilation parameters highlighted in both the uncertainty analysis and in the analysis of specific issues. Thus, for this type of building care must be taken regarding these parameters in the design process, and should also be followed up when the building is set into operation. The input parameters for infiltration, thermal bridges and set temperatures for heating were also identified as critical in the model, in agreement with the experience from the hospital in operation. However, although the same parameters were identified in the model as in the hospital in operation, the modelled changes in HVAC energy usage in the case study were actually higher than measured. Thus, some of the probabilistic distributions for the input parameters have probably been given a too high value. In the remainder of the pilot phase, the probabilistic distributions for the input parameters will be refined, in order to provide a good starting point for future projects.

With respect to the statistical methods applied in the case study, the results presented for case 3 clearly showed that taking correlation between input parameters into account is crucial for correct interpretation of the results for multi-zone buildings. Grouping input parameters and thus assuming full correlation between input parameters across zones lead to more than doubled variance in the projected change in HVAC energy usage. This topic has been given limited attention in the literature and should therefore be followed up in future studies.

Conclusions

This study has presented a framework and methodology that should make it feasible for practitioners working on BPS to get insight into the complex interactions between input parameter variations and model output in their daily workflow. This type of understanding is necessary to address the increasing gap between projected and measured energy usage in buildings. Through a case study for a hospital it has been shown how introducing state-of-the-art global uncertainty and sensitivity analysis in the workflow can give a different level of actionable understanding than approaches often applied today.

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