SIMULATION-BASED ANALYSES AND EVALUATION OF OPERATIONAL FAULTS IN BUILDING TECHNOLOGY

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ABSTRACT

This paper investigates the performance gap in existing buildings. The performance gaps are usually less often found in constructional factors and more often found in building technology and its automation due to hydraulic and control engineering problems. The introduced methodology, coupling a Monte-Carlo approach with building performance simulations is applied to identify the main factors influencing energy-efficient building and system operation. Moreover, the effects of operating faults are quantified based on sensitivity and uncertainty analyses. The main finding is that operational faults in building technology systems have major implications on building operation and result in performance gaps.

INTRODUCTION

Background and Problem Definition

In order to achieve the German national climate protection targets, by 2050 the primary energy demand must be decreased by 80 % of the 2008 levels. In addition, building stock of all types have to become almost climate-neutral (BMWi, 2016). However, the construction of climate-neutral buildings cannot compensate for the ecological footprint of existing building stock. The new build construction rate in Germany is around one percent (Kirchner et al., 2018), which means that 70 % of the 2050 building stock already exists. Therefore, energy saving potentials in these buildings must be identified as well as exploited and building technology plays an essential role in this task.

Particularly in non-residential buildings, the requirements for thermal comfort and user satisfaction as well as productivity factors are very demanding, which means exact conditioning of the interior climate is necessary. This in turn means it is necessary to install extensive technical building equipment. The various influences, such as weather conditions and user behaviour, make the use of additional Building Automation and Control Systems (BACS) as well as regulation functions indispensable to operating building technology efficiently.

Accordingly, not only energy-efficient, but also correct and fault-free operation of the system as well as further operational optimisation of the building technology is necessary. However, this is often not the case and the consumption as well as proposed target figures from the planning process differ considerably from the values measured in the operating phase. This discrepancy is referred to as the performance gap (PG). The causes are generally less frequently problems arising from construction but rather operating faults in the building technology and especially its automation (Auer, Lauss et al., 2020; Dronkelaar et al., 2016). In this context, according to the International Energy Agency (IEA), a fault is generally described as “unpermitted deviation of at least one characteristic property or parameter of the system from acceptable/usual/standard condition” (Dexter et al., 2001). As a result, increased energy and resource consumption, dissatisfied and unproductive users due to thermal discomfort and limited quality of interior environment, system malfunctions and even supply interruptions as well as rising operating costs and increased CO_2 emissions can occur.

Motivation and Task

The original goal of erecting a building that functions perfectly for the users, including low energy requirements and the use of cost-effective building technology, is often not attained. Consequently, a considerable quality risk exists for investments in energy efficiency and user satisfaction in the life cycle of buildings due to the resulting performance gap. This large energy saving potential must be exploited to achieve our climate protection goals.

To this end, we introduce a methodology to analyse and evaluate operating faults in building technology systems and to optimise building performance. Furthermore, we identify the essential influencing parameters and adjusting screws for energy-efficient building and system operation. Based on this, the effects of operating faults in the technical building equipment will be examined in their entirety and energy saving potentials quantified. For these investigations, a model-based procedure is developed and applied to explore the effects of operation faults in the context of the performance gap. Stochastic building models are created with consideration of uncertain boundary conditions, and different operational faults are implemented. The detailed, dynamic building performance simulations

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(BPS) in combination with uncertainty and sensitivity analyses are intended to show the overall effect of operating faults and parameter uncertainties.

METHODOLOGY

Heating, ventilation and air conditioning (HVAC) systems are not subject to a fixed system scheme, but differ in the type and number of components installed and their level of automation. For example, in the case of air handling units (AHU), the DIN EN 16798 differentiates between nine system configurations that can assume various thermodynamic functions. Besides the composition of the components, the type of dimensioning and control strategy of the components offer further possibilities for variation.

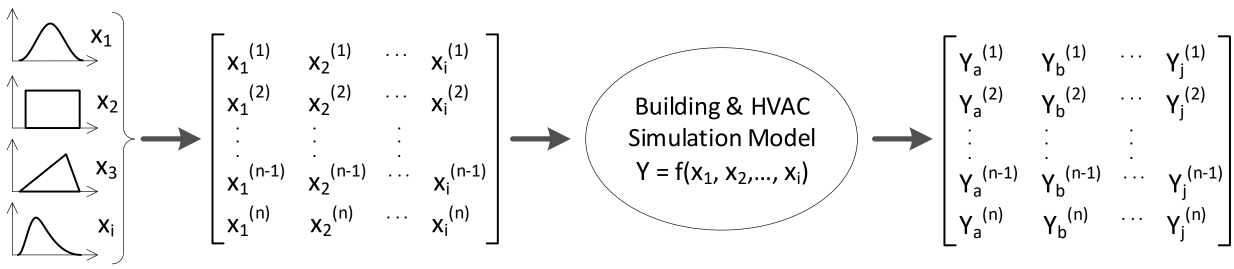
Because many correct operating states can occur in building technology, a large number of parameters move within a value range and should not be regarded as static or fixed numbers. To map these dynamics, a process should be established that allows the statistical variation of different input parameters and analysis their impact on building performance. The same applies to the stochastic fluctuations of operational faults, such as variance, frequency or probability of occurrence. However, the result is not only influenced by the operating fault itself, but also by the states of the other parameters. Monte-Carlo simulations (MCSs) combined with sensitivity and uncertainty analyses are used at this point to represent the wide range of correct operating conditions and faults as well as to determine the results (Y´s) by variation in the input parameters (x´s). Figure 1 represents the workflow for MCSs employed in this paper.

Monte-Carlo simulations are a stochastic method in which random experiments are carried out very frequently, to solve problems numerically that cannot be solved analytically with the help of probability theory. The frequent repetitions of the sample-based simulations are the starting point for generating a distribution of the output. It follows that the examined target variables cannot be assigned to a single correct result, but change dynamically depending on the input parameters and have a probability distribution. Therefore, an MCS is used to prepare the uncertainty analysis of the output Y and the expected value μ (1), the standard deviation σ (2) and the variance V (3) are determined by the following equations:

$$\mu(Y) = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$\sigma(Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} [x_i - \mu(Y)]^2} \tag{2}$$

$$V(Y) = \frac{1}{n}\sum_{i=1}^{n} [x_i - \mu(Y)]^2 \tag{3}$$



Uncertainty and Sensitivity Analyses in Building Performance Simulations

In BPS the influence of individual input parameters (x´s) on the target variables (Y´s) is often unknown. In this regard, general methods that investigate relationships between information from input variables and output variables of a model are defined as sensitivity analyses (SAs). In order to identify the essential set screws and potentials, the SA provides a ranking of the most influential parameters based on the inputs. Within the scope of this paper, SAs are carried out in two steps. The first step is to determine the relative sensitivity of all input parameters. For this purpose all parameters are equally weighted and the same standard deviation of +/- x % is defined for all expected values of the inputs. This makes it possible to get a feel for the model and to determine the relative influence of each parameter. The second step is the specific sensitivity analysis, where the standard deviations of all input parameters are adapted to the real conditions of the examined process or experiment. The resulting scatter of the output due to the variation of the input parameters is considered as the uncertainty of the model. The uncertainty analyses (UAs) quantifies the total uncertainty of the result of a model and is a measure of the robustness of a system. The principle and procedure of a sample-based UA is divided into several steps. The input parameters (x´s) are assigned a probability distribution (e.g. normal N, uniform U, triangular T or logarithmic L). Values are then selected from this distribution using so-called sampling methods and are integrated into the model. By repeating the simulations frequently, a distribution of the target values (output) Y´s is created. This distribution Y is interpreted as the model uncertainty. The uncertainties are quantified using the known statistical estimators for the expected value and the standard deviation or variance. However, visualisations of the model output using density and distribution functions or box-plots are more suitable.

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Simulation Setup

In this paper, a simulation setup is designed and applied, which essentially represents the interaction of three different softwares. Firstly, the software "Plancal Nova", a CAD/CAE-software for building technology, is used to set up and create an exemplary object of investigation with the corresponding systems engineering. The floor plans, 3-D views and technical building system diagrams are designed. In addition, the pre-defined geometric and building physics inputs as well as specifications are used to calculate the heating load and the heat output systems. Afterwards, the software “R-Studio” with the R programming language is used for pre-processing with the calculation of the probability distributions for the input parameters, the creation of a sample matrix and the transfer of the values into the simulations. The building and plant model for the dynamic thermal simulations is created in the “IDA Indoor Climate and Energy” (ICE) software. Firstly, the floor plans and calculated objects in Plancal nova are imported into IDA-ICE and then the thermal behaviour of the buildings is realistically mapped. All systems for building operation – heating, ventilation, cooling and lighting with all relevant control algorithms – are mapped in the model. IDA-ICE works with text files to transmit inputs in the Graphical User Interface to the DAE-Solver. It is possible to change the input of the variables in R-Studio based on the pre-processing. The simulations and processing of the simulation matrix are performed by coupling the software R-Studio with the building and HVAC simulation program IDA-ICE multiple times. The results of each simulation are written into separate output files and are then prepared by post-processing in R-Studio. The final sensitivity and uncertainty analysis of the target variables takes place following the previous steps.

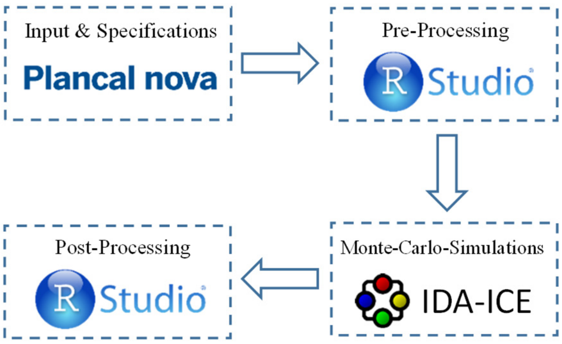

Figure 2: Workflow and simulation setup

This simulation setup, shown in figure 2, allows the coupling of a Monte-Carlo approach with building performance simulations and a workflow for the automated analyses as well as evaluation of the performance of HVAC systems.

CASE STUDY

The application of the methodology is now demonstrated with a case study. The aim is to identify the main factors influencing the energy-efficient operation of air conditioning systems and to quantify the effects of operating faults in AHU´s.

With regard to the operating faults to be investigated in this paper, our research project (Auer, Lauss et al., 2020) identified some irregularities and problems in the operation of AHU´s in non-residental buildings: under-/overrun of the defined operating time (Fault 1/Fault 2), deviation (too high/too low) of supply air temperature from setpoint (Fault 3/Fault 4) and sticked bypass damper (Fault 5).

These investigations form the basis of the considered as well as the simulated operational faults and the derived fault characteristics are implemented in the building and HVAC simulation model. The simulations thus generate synthetic operating data that reflect correct operation of the simulated system followed by the targeted implementation of pre-defined operating faults and subsequent MCSs as well as evaluation with UAs/SAs.

Building and HVAC Simulation Model

The building model is based on a typical three storey office building, which represents the average of this category for non-residental buildings in Germany (Deilmann et al., 2013). The model structure is based on the boundary conditions of the usage profile for group offices according to DIN V 18599-10. The focus of the investigations is on systems engineering and its automation, which is why we chose office buildings with an appropriate level of technical equipment. The energy standard is thus based on a corresponding building age class, and the building model is based on the building physics parameters of the EnEV 2009 for the typical construction structures. A gas condensing boiler provides the heating energy for room heating and for conditioning the supply air in the heating coils of the AHU. In order to investigate the thermodynamic processes of the three air treatment functions, i.e. heating, cooling and dehumidifying, ventilation systems are modelled as partial air conditioning systems (see Figure 3). The AHU is based on VDI 6009-1 and is designed with constant air volume (CAV) and constant supply air temperature control. According to (Werner et al., 2008) partial air conditioning systems are also used three times as often as full air conditioning systems in office and administration buildings. A compression refrigeration machine provides the cooling demand for the cooling coil in the AHU.

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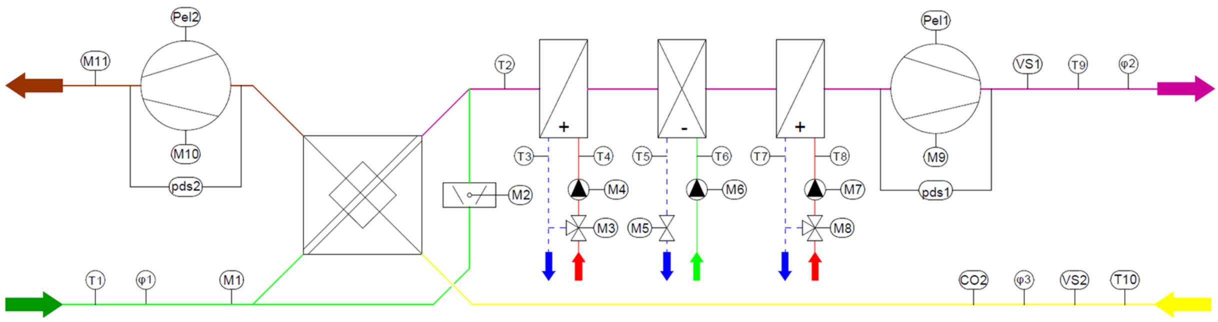

*Figure **3**: Schematic drawing of investigated AHU*

Pre-Processing

The selection of the input parameters for the MCSs as well as SAs and UAs is based on the test object and its HVAC simulation model. Based on the AHU system configuration, all constructive (e.g. structural and design) and scenario (e.g. control and operational) uncertainties are selected as input variables. These set screws for the correct operating conditions are listed in table 1. The probability density functions are based on normative foundations as well as planning and design criteria.

Table 1: Input parameters and probability density functions correct operating conditions

NO.	**INPUT-PARAMETER**	**DISTRIBUTION (μ ; σ) / (min ; max)**
x1	Heat Recovery Efficiency AHU [-]	x1 ~ N(0.55 ; 0.097) → range: 0.34 – 0.78
x2	Setpoint Icing Protection Controller [°C]	x2 ~ N(3.00 ; 0.776) → range: 1.10 – 4.90
x3	Pressure Loss Supply Air [Pa]	x3 ~ N(1325 ; 184.394) → range: 879 – 1771
x4	System Efficiency Fans [-]	x4 ~ N(0.55 ; 0.058) → range: 0.43 – 0.69
x5	Switch-On Time AHU [h]	x5 ~ U(5.00 ; 7.00)
x6	Switch-Off Time AHU [h]	x6 ~ U(18.00 ; 20.00)
x7	Setpoint Supply Air Temperature [°C]	x7 ~ L(18.00 ; 1.553) → range: 18.02 – 22.13
x8	Pressure Loss Exhaust Air [Pa]	x8 ~ N(795 ; 118.401) → range: 509 – 1081
x9	Volume flow AHU [l/s*m²]	x9 ~ N(1.097 ; 0.114) → range: 0.82 – 1.37
x10	Flow Temperature Heating Coils [°C]	x10 ~ N(70.00 ; 3.882) → range: 60.6 – 79.4
x11	Flow Temperature Cooling Coil [°C]	x11 ~ L(6.00 ; 3.106) → range: 5.08 – 14.02
x12	Heat Generator Efficiency [-]	x12 ~ L(0.89 ; 0.043) → range: 0.81 – 0.98
x13	Energy Efficiency Ratio Cooling Machine [-]	x13 ~ N(4 ; 0.388) → range: 3.06 – 4.94

The first step is to determine the relative influence and sensitivity of each input parameter. The same percentage uncertainty is hence defined for each parameter and all expected values are assigned a standard deviation of +/- 10%. The selected standard deviation of +/- 10 % allows remaining within a realistic value range with all inputs. In the second step, the specific sensitivity analysis is carried out, and the assignment of the probability distributions of the input parameters are adapted to the real conditions as well as possible planning bases and operating states of air conditioning systems (see Table 1). The operational faults of the input parameters and probability density functions, shown in table 2, are then implemented. Thus, to ensure comparability each input parameter is given the same probability of occurrence; the faults therefore occur permanently and over the same time period.

Table 2: Input parameters and probability density functions operational faults

NO.	**INPUT-PARAMETER**	**DISTRIBUTION (MIN ; MAX)**
x5 x6	Fault 1: overrun defined operating time AHU [h]	on ~ U(0.00 ; 5.00) off ~ U(20.00 ; 24.00)
x5 x6	Fault 2: underrun defined operating time AHU [h]	on ~ U(7.00 ; 12.50) off ~ U(12.50 ; 18.00)
x7	Fault 3: too high supply air temperature [°C]	x7 ~ U(22.00 ; 26.00)
x7	Fault 4: too low supply air temperature [°C]	x7 ~ U(14.00 ; 18.00)
x14	Fault 5: (sticked) bypass damper position [-]	x14 ~ U(0.00 ; 1.00)

Subsequently, values are selected from these distributions with the help of so-called "sampling" and integrated into the simulation models. A sample matrix is created by selecting (sampling) a point n times from the distributions of the various parameters. We use the "sobol" sequence from the package "randtoolbox" of R-Studio to generate the samples. Sobol sequences produce samples that are distributed as evenly as possible in the multidimensional parameter space. The random numbers are chosen taking into account the numbers already "drawn" to prevent accumulations and gaps in the parameter space. Thus the MCSs converge faster than when using other methods for drawing the sample (Burhenne et al., 2011). In building simulations, 100 runs or samples is often used to map the distributions with sufficient accuracy; a higher number of samples does not lead to greater accuracy (MacDonald, 2009). In this paper, for every simulation, 120 samples per parameter are created, resulting in a sample matrix with 120 rows and 13 columns (one column per parameter x1-x13) for the

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correct operating conditions and 14 columns for operational fault 5 (x1-x13 + x14). In total 840 simulations are carried out for all research purposes.

Monte-Carlo Simulations

A software environment from the building simulation, IDA Indoor Climate and Energy (ICE), is used to create the thermal building and HVAC simulation model. The aim of the simulation is to depict the building as complete system and to map the dynamic reactions between building and systems engineering by means of detailed annual load profiles for rooms, HVAC systems as well as heat and cold generators using the multizone simulation application.

Post-Processing

In post-processing the uncertainty analysis of the target variables (TVs) and the sensitivity analysis for the identification of the essential influencing variables for an energy-efficient HVAC operation takes place. R and several R packages are also used again: R thus acts as system master for the whole workflow including pre-processing, simulations as well as post-processing and is controlled by scripting in this development environment.

Model uncertainties are analysed and evaluated on the basis of the TVs, which are divided into four impact categories to offer a closer look at different effects of the performance gap: first the Energy PG (effects on energy demand), second the Comfort PG (effects on thermal comfort, user satisfaction and productivity factors), third the Ecological PG (effects on greenhouse gas emissions) and fourth the Economical PG (effects on life cycle costs):

- Energy PG: total primary energy demand [kWh/m²a] (TV1), primary energy demand of AHU [kWh/m²a] (TV2)
- Comfort PG: lost work hours (if operative temperature > 25 °C or < 20 °C = performance loss of 2 % per degree) (Wyon, 2000) [h/a] (TV3), over- and undertemperature degree hours (otdh=TV4 / utdh=TV5) [kh/a] according to DIN EN 15251 of critical zones (odth=west, utdh=norht-east) determined by the following equations:

$$\text{otdh} = \sum |\, T_{Op} - T_{Level,ot} \,| * t \quad (4)$$

$$\text{utdh} = \sum |\, T_{Level,ut} - T_{Op} \,| * t \quad (5)$$

- Ecological PG: total CO_2 emissions (standard market values used) [kg CO_2/m²a] (TV6)
- Economical PG: total energy operating costs (market-based prices used) [€/m²a] (TV7)

The evaluation of the uncertainty analysis with graphical representation is based on scatter-plots, histogramms, box-plots and Q-Q-Plots. For this purpose, histograms are used to illustrate the distributions, and the normal distribution is demonstrated by means of the two control graphics box-plots or Q-Q plots. For all target variables, the calculation of mean value μ, standard deviation σ as well as variance V is conducted and this results in the total uncertainty around the expected value TUNC_ μ determined by the following equation:

$$\text{TUNC\_}\mu = \frac{\sigma}{\mu} * 100\ \% \quad (6)$$

Based on the case study, three methods are used to determine the sensitive input parameters and will be compared due to the different application for linear and non-linear correlations. First, the correlation coefficients according to Pearson and Spearman are calculated, followed by the regression analysis using SRC, SRCC, PCC and PCC and the the final graphical evaluation of scatter plots are coupled with “Conditional Variances - Second Path” (Saltelli et al., 2008).

RESULTS AND DISCUSSIONS

The results presented below are divided into three subsections: relative sensitivity analysis, specific uncertainty analysis and specific sensitivity analysis.

Relative Sensitivity Analysis

The results of the preliminary study for the specific sensitivity analysis are described below. This first analysis offers an initial impression of the model and determines the relative influence of the parameters examined. For this purpose, the same standard deviation and thus an uncertainty of +/- 10 % is assigned for all expected values of the individual input parameters, which means that the information on the relative SA is only conditionally reliable and only correct operating conditions are considered. The results in table 3 show that, almost independent of the method used for the sensitivity analysis, the parameters x9 “Volume Flow AHU”, x1 ”Heat Recovery Efficiency” and x7 “Supply Air Temperature” as well as x4 “System Efficiency Fans” have the greatest influence on the model in terms of TV 2 “Primary energy demand AHU”.

Table 3: Ranking of relative SA for Energy PG (TV2) with correct operating conditions

TV2	SPEAR. / SRCC	PRCC	V (*10³) [kWh/m²a]
# 1	x9 (0.56)	x9 (0.89)	x9 (16.67)
# 2	x1 (-0.38)	x1 (-0.78)	x7 (8.37)
# 3	x7 (0.36)	x7 (0.76)	x1 (7.25)
# 4	x4 (-0.30)	x4 (-0.74)	x4 (7.22)
# 5	x5 (-0.27)	x3 (0.63)	x3 (6.37)
# 6	x3 (0.26)	x6 (0.58)	x5 (5.94)

The analysis of relative SA did not reveal any substantial differences between the two evaluation pairs Spearman/SRCC and Pearson/SRC. In addition, examining PRC instead of PRCC also does not produce a shift in the rankings, and thus the

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ranking is representative for all evaluation methods. The evaluations of the Comfort PG (TV3-TV5) indicated that the AHU operating time (x5 on / x6 off), supply air temperature (x7) and volume flow AHU (x9) as well as flow temperature heating coils (x10) are the most sensitive input parameters. Ecological PG (TV6) and Economical PG (TV7) are most influenced by volume flow AHU (x9), flow temperature cooling coil (x11), switch-on time AHU (x5) and the fan system efficiency (x4) as well as the heat generator efficiency (x12).

Specific Uncertainty Analysis

In this investigation, all input parameters are adapted to the respective properties and a defined standard deviation is assigned (see Table 1). Within the framework of the Monte-Carlo analysis, 720 simulations are carried out to map correct and faulty operating conditions with the developed building and HVAC model. Figure 4 presents the results of the UA for correct operating conditions using the TV 2 “Primary energy demand AHU”.

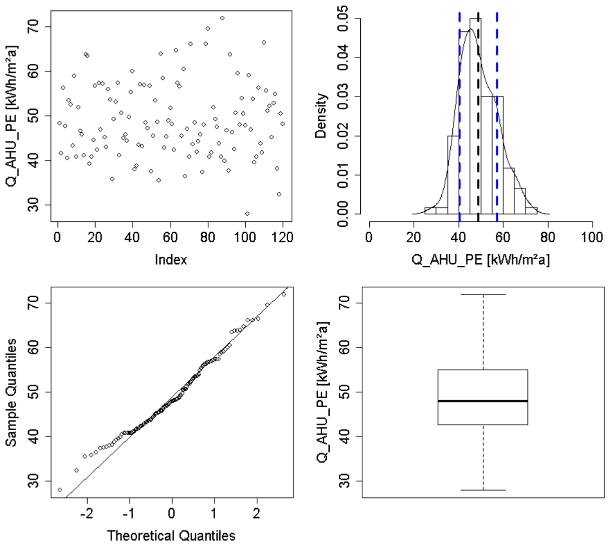

Figure 4: Evaluation of UA for Energy PG (TV2) with scatter-plot, histogram, Q-Q plot and box-plot

The scatter-plot represents the graphical visualisation of observed value pairs of two statistical characteristics; for each of the 120 simulations, a result value is entered for the TV2. The histogram shows the graphical representation of TV2 with a frequency distribution based on the variation of different input variables and the calculated expected value (black dotted line) as well as the standard deviation (blue dotted lines). The two control graphs, Q-Q Plot and box-plot, are used to determine if an existing normal distribution exists. Since no errors or outliers can be detected in the diagrams, a normal distribution is assumed below. An expected value of 48.9 kWh/m²a is calculated for TV2 and the standard deviation of 8.4 kWh/m²a is used as a measure of uncertainty. Thus, the variation of the uncertain boundary conditions of constructive (e.g. structural and design) and scenario (e.g. control and operational) uncertainties, with regard to correct operating conditions, results in a total uncertainty of 17.1 % around the expected value. Table 4 shows the target variables for the investigation of the Energy PG (TV1&TV2), Comfort PG (TV3-TV5), Ecological PG (TV6) and Economical PG (TV7) in the fault-free cases using the evaluation criteria of expected value μ, standard deviation σ, variance V and total uncertainty of around the expected value TUNC_ μ.

Table 4: UA with correct operating conditions

TV NO.	μ	σ	V	TUNC_μ
TV1	191.9	9.3	85.9	4.8
TV2	48.9	8.4	70.2	17.1
TV3	391.9	59.3	3514.7	15.1
TV4	536.6	51.9	2688.7	9.7
TV5	398.8	90.7	8222.3	22.7
TV6	77.8	3.2	10.1	4.0
TV7	9.4	0.4	0.2	4.3

A total of 580 simulations are performed as part of the MCS to analyse and evaluate the operating faults. Figure 5 shows the evaluation of the TV2, and in combination with all TV´s in table 5 & 6 the faults are compared with the correct operating conditions based on the defined evaluation criteria.

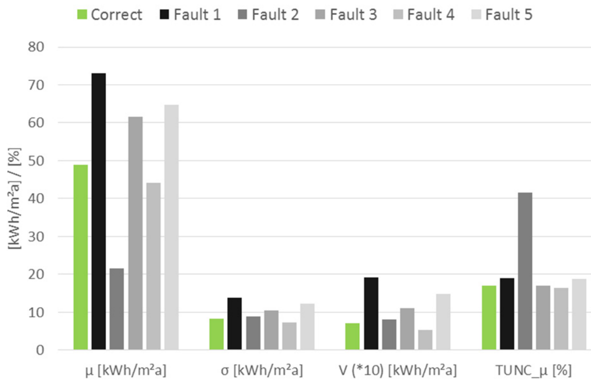

Figure 5: UA for Energy PG (TV2) correct vs. faults

Fault 1 “overrun defined operating time AHU” causes the greatest impact related to Energy PG as well as Ecological PG and Economical PG. For TV2 the additional energy demand in terms of the expected value is about 50 % above that for correct operating conditions. Fault 2 “underrun defined operating time AHU” would reduce the primary energy demand in AHU plant operation (TV2) by more than half compared with the fault-free reference, or approx. 15 % on the total primary energy level (TV1). This result however is counterbalanced by the analysis of all influencing factors on the PG. When looking at the Comfort PG, the effects of fault 2 are significant losses in the form of increased lost work hours (TV3) as well as increased over- (TV4) and undertemperature degree hours (TV5). In overall terms, the energy savings due to fault 2 would not compensate for the greatly reduced thermal discomfort as well as limited quality of interior environment, and would lead to additional

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costs in the overall calculation. Fault 3 “too high supply air temperature” and fault 5 “sticked bypass damper” have similar effects and cause an Energy PG of about 30 % above compared to the correct operating conditions and also lead to an increase in Ecological PG and Economical PG. Regarding fault 4 “too low supply air temperature”, an energy saving of approx. 10 % compared to the reference can generally be determined for the system boundary AHU (TV2); however, the interactions between the building technology systems must also be taken into account here. Consequently, fault 4 leads to an increased total primary energy demand (TV1); the excessively low supply air temperatures must be compensated for by the increased heat output of the static heating surfaces. This scenario also increases the Ecological PG and the Economical PG.

Table 5: Expected values μ with operating faults

μ	C	F 1	F 2	F 3	F 4	F 5
TV1	191.9	225.3	161.9	196.1	194.4	207.9
TV2	48.9	73.0	21.6	61.7	44.2	64.8
TV3	391	218.6	437.6	417.2	365.1	392.4
TV4	536	711.4	555.8	749.1	380.7	532.2
TV5	399	83.7	493.5	351.1	441.5	399.7
TV6	77.8	88.7	66.9	78.1	79.1	81.6
TV7	9.4	10.8	8.0	9.5	9.5	10.0

Table 6 shows the evaluations of the standard deviations for all target variables in the particular fault case in comparison with the correct operating conditions. The resulting total model uncertainty around the expected value is calculated by dividing the two variables σ/μ and is described by equation 6.

Table 6: Standard deviations σ with operating faults

σ	C	F 1	F 2	F 3	F 4	F 5
TV1	9.3	15.4	10.0	10.6	9.1	13.4
TV2	8.4	13.9	9.0	10.5	7.2	12.2
TV3	59.3	28.4	63.7	52.3	66.7	59.6
TV4	51.9	71.9	70	31.7	70	53.9
TV5	90.7	38.1	94.3	85.5	97.1	90.7
TV6	3.2	5.2	3.6	3.3	3.2	3.8
TV7	0.4	0.7	0.5	0.4	0.4	0.5

Specific Sensitivity Analysis

Once the model uncertainties are established, a sensitivity analysis is carried out to determine the relevant parameters. Due to the unlimited application possibilities, the focus of the evaluations is on scatter plots; it does not matter whether a linear/non-linear or monotonous/non-monotonous relationship exists in the data. In addition, SAs using Spearman/SRCC and linear regression using PRCC are also performed. Figure 6 shows two SA results using the scatter-plot method. The uncertainty of input parameter x1 “Heat Recovery Efficiency” on the x-axis and TV2 on the y-axis are plotted on the left side and x12 “Heat Generator Efficiency” and TV2 are compared on the right side. A uniformly distributed scatter-plot means no correlation and a non-uniformly distributed plot is considered a correlation; so the two variables, TV2 and input x1, show a clear correlation. The other parameters TV2 and x12 do not exert a strong influence. This finding can be confirmed using the other SA evaluation methods (see Table 7).

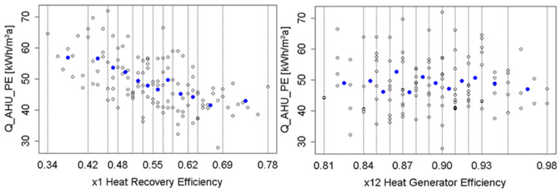

Figure 6: SA with variance analysis "Conditional Variance" algorithm for Energy PG (TV2)

The algorithm “Conditional Variances - Second Path” is used to create a ranking of the input parameters by dividing the results of the scatter-plots into ten equally sized areas and calculating the mean values of the output for each area (blue points). By scattering the ten mean values, a variance of the target variable in connection with the respective input parameter can be calculated. Table 7 lists the ranking of the most sensitive input parameters for TV 2 “Primary energy demand AHU” in terms of correct operationg conditions.

Table 7: Ranking of specific SA for Energy PG (TV2) with correct operating conditions

TV2	SPEAR. / SRCC	PRCC	V (*10³) [kWh/m²a]
# 1	x1 (-0.58)	x1 (-0.91)	x1 (22.04)
# 2	x9 (0.50)	x9 (0.89)	x9 (19.14)
# 3	x5 (-0.29)	x4 (-0.74)	x5 (10.32)
# 4	x3 (0.29)	x3 (0.72)	x3 (8.50)
# 5	x4 (-0.25)	x6 (0.68)	x4 (7.12)
# 6	x6 (0.24)	x8 (0.57)	x7 (5.17)

Based on the specific SA for correct operating conditions and the results in table 7, the parameters x1 “Heat Recovery Efficiency”, x9 “Volume Flow AHU”, x5 “Switch-On Time AHU” and x3 “Supply Air Pressure Loss” have the greatest influence on the model output TV2. The varying results compared to relative SA can be explained as follows: x7 “Supply Air Temperature” now plays a subordinate role, since the value range has been adapted to real conditions and accordingly extends over a smaller range. In contrast, x1 is now significantly more influential and the most sensitive parameter, due to its extended value range. The ranking of the most sensitive inputs for the second target variable of the Energy PG (TV1) resulted in the same parameters as shown for TV2 in table 7, with only a slight shift in the order. In the analysis of the target values for the Comfort PG (TV3-TV5), the following input parameters are calculated with the greatest variance: AHU operating time (x5 on / x6 off), volume flow AHU (x9) and the flow temperatures of heating (x11) / cooling (x10) coils. For the Ecological PG (TV6) and Economical PG (TV7) the same sensitive input parameters are obtained as for the Energy PG with almost the same sequence as shown in table 7.
Our method for evaluating the sensitivity indices with the algorithm "Conditional Variances - Second

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Path" is also applied for the SAs of the operating faults. Table 8 shows the ranking of the most sensitive input parameters for the respective fault case.

*Table 8: Ranking of specific SA with operating faults for Energy PG (TV2) by variance analysis (V *10³)*

	F 1	F 2	F 3	F 4	F 5
# 1	x1 (57.9)	x6 (42.5)	x1 (31.9)	x9 (13.6)	x14 (68.3)
# 2	x9 (43.6)	x5 (25.9)	x9 (28.6)	x1 (13.0)	x11 (35.8)
# 3	x5 (38.8)	x7 (18.7)	x5 (18.7)	x5 (8.0)	x9 (33.5)
# 4	x3 (21.3)	x8 (15.3)	x7 (16.1)	x3 (7.0)	x8 (33.1)
# 5	x6 (19.5)	x10 (10.3)	x3 (11.1)	x4 (6.8)	x3 (25.9)
# 6	x4 (16.6)	x13 (6.9)	x11 (8.9)	x6 (4.7)	x5 (16.9)

In the sensitivity analysis with operating faults, regardless of the fault case, the input parameters x1, x9 or x14 and the operating time (x5, x6) with the switch-on time in the foreground have the highest priority for the scatter of TV2. The results also show that the fan system efficiency (x4) and the pressure drop on the supply (x3) and exhaust air side (x8) also have a significant influence on the variance of TV2.

CONCLUSION AND OUTLOOK

Our methodology, coupling a Monte-Carlo approach with building performance simulations, enabled identifying the essential input parameters for the energy-efficient and comfort related building and HVAC operation and quantifying the effects of operating faults. Based on sensitivity and uncertainty analyses, the major impact of operating faults on building and system operation reveals that the technical gap is one of the main drivers for performance gaps. Our study enhances academic and practical understanding of the factors influencing operational optimisation of building technology systems and improving energy efficiency as well as the user comfort in existing buildings. Moreover, future processes for energy and efficicency related quality assurance in building operation should take into account the discussed results and findings gained within the framework of this research. In this way a contribution to the development of an energy-optimised building stock can be made and goes beyond the scope of previous research work dealing within this context.

Future work should involve exploring additional operational faults in building technology systems and identifying fault charactersitcs and profiles which enable more detailed and realistic fault scenarios e.g. consider the frequency of occurrence. Based on the promising findings presented in this paper, work on the remaining issues will be continued and presented in future publications.

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