Energy Performance Contracting Methodology Based upon Simulation and Measurement

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Abstract

Discrepancies between ex-ante energy performance assessment and actual consumption of buildings hinder the development of energy performance contracting (EPC). To address this issue, uncertainty integration in simulation as well as measurement and verification (M&V) strategies have been studied. In this article, we propose a methodology, combining detailed energy performance simulation and M&V anticipation. Statistical studies using Monte-Carlo analysis allow a guaranteed consumption limit to be evaluated according to a given risk. Adjustment and verification procedures are also derived from the simulation results in relation to an optimised measurement plan. The complete process has been tested on a refurbishment project allowing the decrease of the difference between the guaranteed consumption limit and the reference energy consumption from 25 % to 15 % of reference consumption.

Introduction

The building sector is one of the main contributors to final energy use and related environmental impacts worldwide, accounting for 40 % of CO_2 emissions. In order to achieve the French and international energy transition commitments, a mutation needs to occur including a massive retrofitting plan and an increasing energy performance of new buildings. Public and private incentives have been set up to support this movement and encourage investments. Energy services companies (ESCOs) have been developing energy performance contracts (EPC) in order to facilitate project funding by securing operation costs. However, challenges hinder the development of such contracts. We can differentiate constraints related to forecasting model errors, uncertainties on measurement of actual consumption and operating conditions and methodological limitations.

Simulation tools are widely used to predict energy consumption of buildings but several limitations restrict the reliability of their results. Multiple feedbacks show large discrepancies between simulation results and actual consumptions of buildings (Macdonald 2002). Many studies have investigated the causes of these gaps, identifying four main sources of uncertainty on simulation results (Coakley et al. 2014): modelling simplification and hypothesis (building zoning...); partial knowledge on physical parameters including materials, geometry and systems; errors coming from discretisation and numerical solving; occupancy, external and internal loads.

Much research has been conducted on the latter subject, questioning the influence of occupants' behaviour, and weather on energy consumption. Wang (2012) investigated these effect concluding in variations on energy consumption up to 80 %. Hong (2013) highlighted the impact on peak electricity demand of different weather files comparing typical and actual data. The strong variability of energy consumption due to variation of weather and occupancy confirmed by many studies and feedbacks, constitutes one of the main points hindering the development of EPC.

Other issues deal with the measurement and verification (M&V) process. Measurement uncertainties affect energy performance evaluation. They have to be minimised and taken into account in the risk determination (Burkhart et al. 2014). Good practice has to be set up regarding verification of the contract commitments by co-contracting parties. The international performance measurement and verification protocol (IPMVP) proposes a framework to implement such processes (EVO 2012). Four options related to various situations are detailed. In this study, we are mainly interested in cases covered by options C and D of IPMVP. They concern total energy saving respectively in refurbishment projects where a pre-retrofit situation is known, and new building projects for which simulation is the only mean to anticipate building performance. In case of refurbishment projects, IPMVP defines a monitored reference situation allowing the comparison between pre- and post-retrofit situations. In new projects simulation, the baseline is hypothetical and corresponds to an energy consumption in a specific context. In both cases, it is necessary to define different explanatory variables characterising the baseline (e.g. setpoint temperature). Thus, not only energy consumption but also several other physical quantities have to be monitored. Their related uncertainty also influences the performance evaluation.

EPC methodologies plan a contextualisation of energy consumption by adjusting the baseline situation to real conditions. M&V procedures often require ESCOs to update their building simulation model according to measured data. This constitutes a major difficulty and a challenging scientific problem.

This adjustment process and the risk determination in reference conditions are usually performed separately. ESCOs sometimes propose arbitrary limit values to set the guaranteed commitment. These practices highlight the lack of coordination between the different phases of an EPC project. Much research has been conducted on each phase but few consider the complete process composed by interdependent methods.

In this paper, we propose a methodology based upon the statistical analysis of simulation results in order to elaborate a future measurement plan according to an acceptable risk related to energy performance guarantee. This methodology also allows the anticipation of performance adjustment, avoiding the need to re-develop a simulation model after data acquisition during building operation.

Uncertainty and variability analyses methods

Building energy model

A detailed dynamic building energy simulation (DBES) tool, Pléiades+COMFIE (Peuportier and Blanc-Sommereux 1990), was used to run annual simulations. This validated model (Brun et al. 2009) is based on a finite volume approach. Static and dynamic input parameters are needed, including building geometry, thermal properties, internal and external driving forces. Such models are generally used to size HVAC systems, compare the energy efficiency of different design alternatives, or investigate energy conservation measures (ECM) in refurbishment projects. Software plug-ins deal with modelling of HVAC systems and estimating the generation and distribution yields.

Sensitivity analysis

Building simulation is based on a large number of parameters. Output uncertainty comes from both parameters' uncertainty and model sensitivity to these parameters.

Sensitivity analysis identifies influent parameters, and quantifies this influence. Main groups of influent parameters can be determined thanks to Morris method (Morris 1991) with a low computation time. This method's interest also lies on its large area of applicability. No hypotheses of model linearity or about correlated inputs are needed. « Elementary Effects » of parameters variations on outputs are calculated at randomly selected points of the parametric space. The average μ_p^* and standard deviation σ_p of the absolute value of these effects are evaluated for each parameter. σ_p values are related to parameters interactions and non-linear effects. In order to characterise a parameter's influence, the following norm is defined:

$$D_p = \sqrt{{\sigma_p}^2 + {\mu_p^*}^2} \qquad (1)$$

Influent parameters correspond to high D_p values. Following the sensitivity analysis, non-influent parameters are set at their nominal value in the ongoing process.

One way to integrate dynamic inputs into sensitivity analyses is to define a static variability such as a relative or absolute variation modifying the time series. This simplified process is questionable. The strong influence of occupancy (Haldi and Robinson 2011) and weather (Hong et al 2013) on energy consumption has been well demonstrated both numerically and empirically. It is therefore essential to describe a realistic variability of these factors, which have a prevailing impact on building energy consumption.

Stochastic occupancy model

To deal with users influence, the model proposed by Vorger et al. (2014) was used in the present study to generate realistic inhabitants' characteristics and behaviour. Multiple statistical data were studied to build this model, e.g. the French census results. A stochastic process sets users' characteristics and presence scenarios. The corresponding activities influence internal loads, windows use, and hot water consumption profile. Figure 1 presents an internal gains average scenario in a four inhabitants flat during a week derived from a sample of 200 generated scenarios.

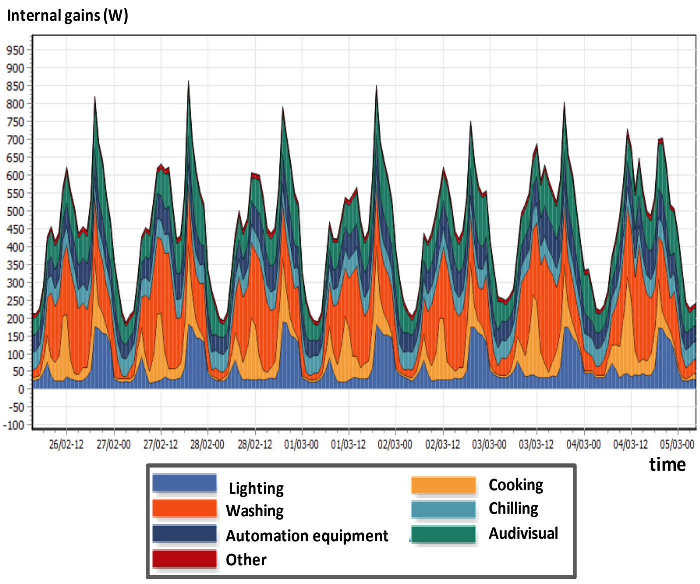

Figure 1: Generated average internal gains scenario in a flat occupied by four inhabitants during a winter week

This model can be used in MC analyses by creating a specific and realistic set of inhabitants, and their associated presence and activities scenarios for each simulation.

Weather natural variability

A model generating artificial meteorological year (AMY) files was developed to describe the natural variability of weather conditions. This model, derived from Boland's work (Boland 1995), creates annual hourly time series of dry bulb outdoor temperature (T), global horizontal irradiation (GHI) and diffuse horizontal irradiation (DHI). These data sets were created from a unique typical meteorological year (TMY) file depicting the weather of the building project site. Rastogi (2016) developed a similar AMY generator differing in the generation process of irradiation series.

In the model used in this study and described in Figure 2, generated T and GHI time series are the sum of a deterministic and a random time series. Deterministic components are identified from a Fourier decomposition of TMY time series keeping the significant harmonics, which are the annual mean, one cycle per year and one cycle per day. By subtracting Fourier series to the original data, we obtain residual time series characterising the deviations to the mean trend (Fourier series). This residual series can be fit with a Seasonal Auto-Regressive Moving Average (SARMA) model depicting its auto-correlation. We created random time series using this SARMA model from randomly generated white noises. Artificial time series were created by adding this random component to the identified Fourier series.

Temperature data were first generated according to the principle above as shown in step 1 of Figure 2. In a second step, the GHI time series from TMY file was split into a Fourier series and a residual component. T and GHI Fourier series are naturally correlated but it is necessary to correlate both deterministic and random parts of generated data to preserve the complete cross-correlation. We identified a Vector Auto-Regressive (VAR) model, binding the GHI and T daily mean residual time series with the cross-correlation coefficient. In a third step, hourly data were reconstructed from daily mean and hourly extra-terrestrial irradiation series. The VAR model was identified by an iterative process in order to respect the complete cross-correlation between the final time series. By this method, auto-correlated and cross-correlated GHI residuals were generated. DHI time series were derived from generated GHI data according to extra-terrestrial (ET) irradiation and clearness index.

Randomly generated data respected the original auto- and inter-correlation. They were associated to a TMY file and are representative of weather conditions in a specific location. By repeating the identification process on several actual meteorological years (AMY) we observed slight modifications of Fourier coefficients. These variations were integrated in the process by a combined random modification of T and GHI Fourier coefficients in their identified variation ranges.

Uncertainty and variability propagation

The use of variability models is completed by a propagation of uncertainty on static inputs. Probability density functions (PDFs) were define to characterise influent parameters' uncertainty: mainly normal and uniform distributions according to the source of information (Spitz et al. 2012). Random draws were realised within these PDFs using quasi Monte-Carlo sampling. For each dynamic building energy simulation, a specific set of input parameters was used. A Monte-Carlo (MC) analysis including 6000 simulations was carried out to identify the resulting distribution of the quantity of interest: the building energy consumption.

The methodology presented below relies on transformation and statistical exploitation of the results of this large set of building energy simulations.

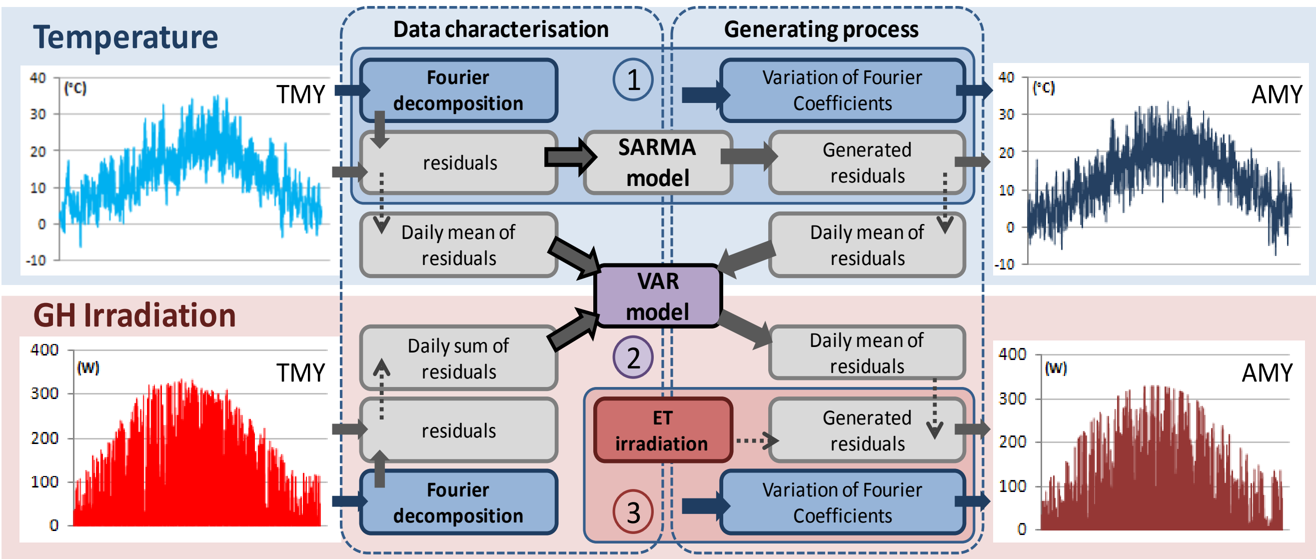

Figure 2: Generation process of auto-correlated and cross-correlated time series of temperature and global horizontal irradiation

EPC methodology

Objectives

The distribution deviation of building energy consumption depends on the uncertainty level of inputs. To reduce this deviation, it is necessary to know input values with more accuracy. Some parameters such as temperature setpoints or outdoor temperature are only known during the operation phase and are related to occupants' behaviour or weather variability and not to the contractor's responsibility (ESCO). By mining MC analysis results, the methodology presented below aims at automatically studying the link between energy consumption and multiple explanatory variables, called adjustment variables (AVs), derived from these parameters. This aims at removing the variability associated to these parameters from the uncertain context on which is based the probabilistic evaluation of energy consumption. Parameters not related to the building quality may have a strong impact on building energy consumption and therefore shall not be associated to the risk taken in ESCOs' commitment. A guaranteed consumption limit (GCL_α) for a risk α will be defined depending on the AVs, in the upstream process. Measurement being conducted during building operation, AVs will be monitored and calculated to perform the GCL_α adjustment. The annual guaranteed consumption limit (GCL_α) obtained by following this methodology is a maximal value of energy consumption set in the EPC. Beyond this value, ESCOs providing the EPC would have to pay the overcost or potential penalty.

Adjustment variables definition

Quantities used to calcutate AVs have to be measurable and not be related to the contractor's responsibility regarding the performance of building envelope and HVAC systems. Moreover, it is appropriate to choose parameters with the largest influence on the variability of energy consumption. A part of these parameters characterising operating conditions are dynamic inputs and are modelled as time series. It is necessary to associate these floating physical quantities to adjustment variables (AVs) to agglomerate the information in single parameters. For example, Heating Degree Days with a baseline of 18°C (HDD_{18}) is a common and simple variable representing the effects of outdoor temperature. Different variables can be derived from a set of data. For example, the average outdoor temperature ($\bar{T}_{out}$) is another AV describing outdoor temperature series. An importance analysis was used to rank AVs according to their link with the quantity of interest, mainly energy consumption (Manfren et al. 2013). We compared root-mean-square error (RMSE) of linear regression models using different sets of AVs in order to identify the most relevant variables.

Adjustment formulation

Several types of metamodels can be considered in order to relate the output to the AVs. In the work presented here, we concentrated on multi-variable linear models though other possibilities could be studied. The simple form of this parametric model allows a better understanding by the co-contractors. In a comparison of metamodels applied to the characterisation of a big set of buildings, Tian (2015) concluded that linear models show strong performance. The adjustment variables must be independent and this hypothesis can be verified with a Student test.

The proposed model provides GCL_α in reference conditions ($GCT_{\alpha-ref}$) and a linear model to adjust this value according to real operating conditions defined by the chosen adjustment variables (AVs).

Reference conditions are set arbitrarily but it is common to choose this reference according to standard conditions or from pre-retrofit measurements when they are available. In the example of an EPC regarding heating consumption in a new building project, reference conditions can correspond to a constant temperature setpoint scenario of 20°C and to weather conditions obtained by a TMY file. The AVs selected in the project can be calculated from these reference conditions.

The proposed adjustment model is given in equation (2) in which the adjusted guaranteed consumption limit $GCL_{\alpha\text{-}adj}$ is formulated relatively to AVs calculated in real (AV_i) and reference conditions ($AVi - ref$).

$$GCL_{\alpha-adj} = GCL_{\alpha-ref} + \sum_{i=1}^{n} a_i \times \left(\frac{AV_i - AV_{i-ref}}{AV_{i-ref}}\right) \quad (2)$$

The a_i coefficients were determined according to the method below describing the mining of MC analysis simulation results obtained by uncertainty and variability propagation.

Adjustment model calculation

The calculation process of the adjustment polynomial of GCL_α as a function of AVs is presented in Figure 3 in the case where only one AV is considered. The general case will be first detailed followed by the specific one dimension case.

Firstly, the polynomial of the mathematical expectation of the energy consumption in terms of AVs is defined by a multiple linear regression. The deviation of the remaining variability around this linear model is not necessarily constant and may depend on the AVs values. This means that the required adjustment polynomial of the GCL_α for a given risk α differs from the one obtained by the multiple linear regression calculated by least-squares method. It is determined by studying the distribution of subsets of the simulations.

Secondly, the mean of each AV distribution is calculated. We define *n*+1 subsets of simulation results, *n* being the number of AVs. The first considered subset includes simulations for which all AVs values are smaller than their respective mean value. In the remaining *n* subsets, all AVs values are also smaller than their mean, except one, AV_i, which is greater than its mean. Thus, n+1 data subsets are defined. For each subset the average values of adjustment variables are computed.

Thirdly, the distribution of the residuals (difference between the energy consumption and its prediction by the mean linear model) is analysed in order to determine by enumeration the (1-α)-quantile in each data set.

Fourthly, the coordinates of the points belonging to the final linear adjustment model were calculated in each subset. Their abscissas are AVs mean values. Their ordinates are composed by the sum of the linear regression at these abscissas and the (1-α)-quantile of the residuals. These coordinates characterise the deviation of the studied subset. We define the coefficients of the adjustment polynomial by associating the points' coordinates of the first group to each other subset's.

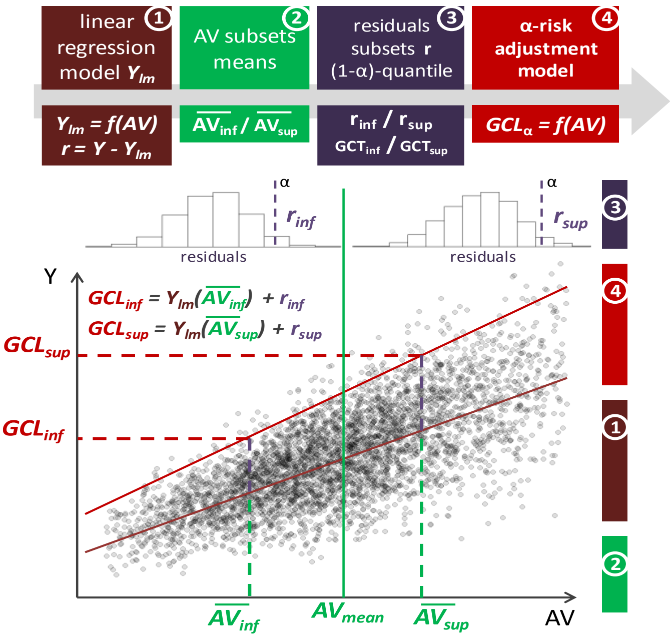

Figure 3: Methodology of the adjustment model determination

Figure 3 illustrates the process in the case where only one AV is taken into account. For each of the two subsets of simulation results, split according AV_{mean}, we calculated the mean values: $\overline{AV}_{inf}$ and $\overline{AV}_{sup}$. We associated an ordinate value composed by the sum of the linear regression result in $\overline{AV}_{inf}$ (resp. $\overline{AV}_{sup}$) and the (1-α)-quantile of the residuals r_{inf} (resp. r_{sup}) of the GCL_α adjustment linear model presented in equation (2) was defined by two coordinates: (GCL_{sup}; AV_{sup}) and (GCL_{inf}; AV_{inf}).

Impact of measurement uncertainties

During building operation, data will be collected all along the commitment period allowing co-contracting parties to calculate the real AVs values and compare the measured energy consumption to the $GCL_{\alpha\text{-}adj}$ calculated thanks to the adjustment model in order to verify the EPC commitment. The measurement uncertainties nevertheless modify the risk level associated to the GCL_α and we propose to anticipate their impact when evaluating GCL_α by a perturbation of simulation results.

Specifying the required measurement plan, measurement uncertainties on adjustment variables (ΔAV_i) and energy consumption (ΔY) can be calculated from sensors' measurement uncertainty. For each simulation, ΔAV_i and ΔY were calculated according to the specific conditions of the simulation. For example, uncertainty on heating degree days (ΔHDD_{18}) depends on the number of considered days which differs according to weather conditions.

For each simulation, random draws were realised in the PDFs defined for ΔAV_i and ΔY, characterising the potential measurement errors. AV_i and Y simulation values were modified taken those errors into account. Thus, we took perturbed data into account to run the EPC methodology described above and to determine the adjustment model as shown in Figure 4 which summarises the complete methodology.

Thus, the EPC methodology can provide a set of necessary elements for the EPC: the measurement equipment specification, GCL_α and AVs values in reference conditions, the adjustment polynomial, and guidelines to measure and verify building energy performance. It allows ESCOs to formalise a complete contract without any need to redefine an ex post BES model matching post-construction or retrofit operating conditions.

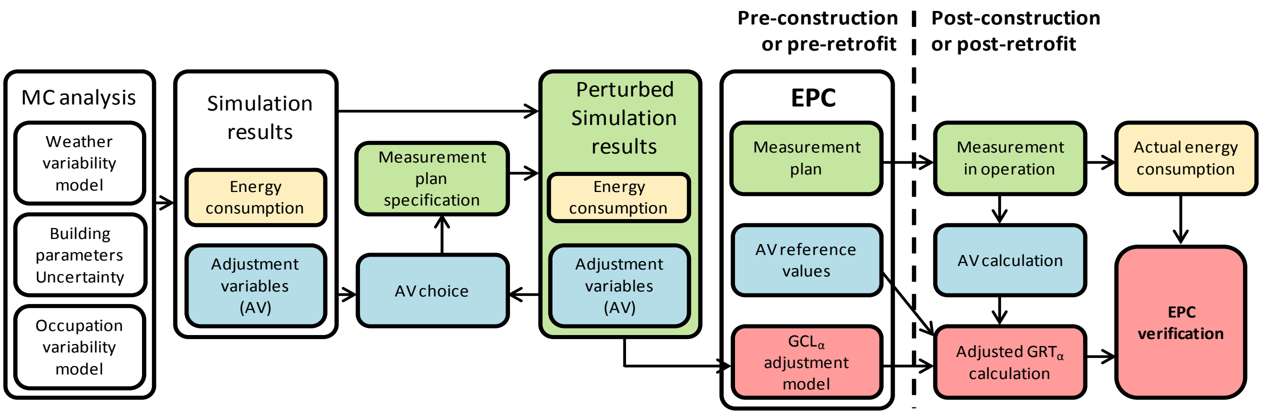

Figure 4: Complete EPC methodology

Results

Description of the case study

The case study consisted in the refurbishment of a residential building composed of 16 apartments on three floors for a total of 1048 m². Retrofitting included insulation improvement, change of heating and ventilation systems, and thermal bridges reduction. This building was modelled using Pléiades+COMFIE, and divided in 17 thermal zones by differentiating each flat and the common area as shown in Figure 5.

The study aimed at proposing a guaranteed consumption limit value of heating and hot water energy consumption of the whole building with a 5 % risk ($GCL_{5\%}$). Measurement campaigns conducted before and after retrofit allowed the methodology to be tested down to the guarantee verification. Details of the building model can be found in Ajib's work (Ajib 2015).

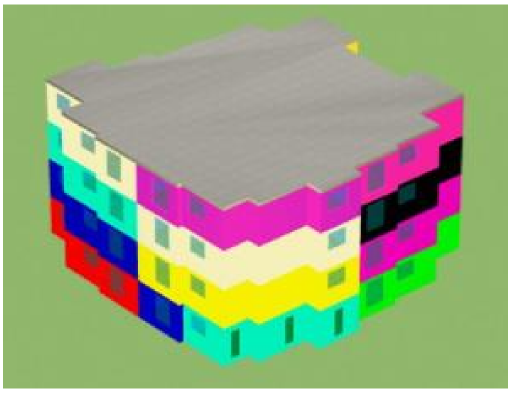

Figure 5: Thermal zones considered in the building

Static and dynamic input parameters

A DBES post-retrofit model was developed according to the refurbishment plan. Occupancy, internal gains, temperature setpoint, and hot water consumption scenarios were set according to pre-retrofit measurements in each flat. They were available in this case study. To complete these reference conditions, we considered the local typical meteorological year (TMY) file of the city of Mâcon (France).

A sensitivity analysis was first conducted using Morris method in order to select influent parameters. 39 uncertain model parameters were listed. Their variation ranges were set by expert knowledge and scientific literature. Variability of dynamic inputs was considered thanks to a relative variation in the sensitivity analysis. Outdoor temperature variability was not included in Morris analysis because of methodological limitation described above. The sensitivity analysis identified 12 influential parameters, ranked according to the norm defined in (1), as shown in Figure 6. The most influential ones were the nominal power of the heating system, which was known with limited accuracy, internal gains, and temperature setpoint. As a matter of fact, the relative variation ranges considered on these last inputs was rather wide.

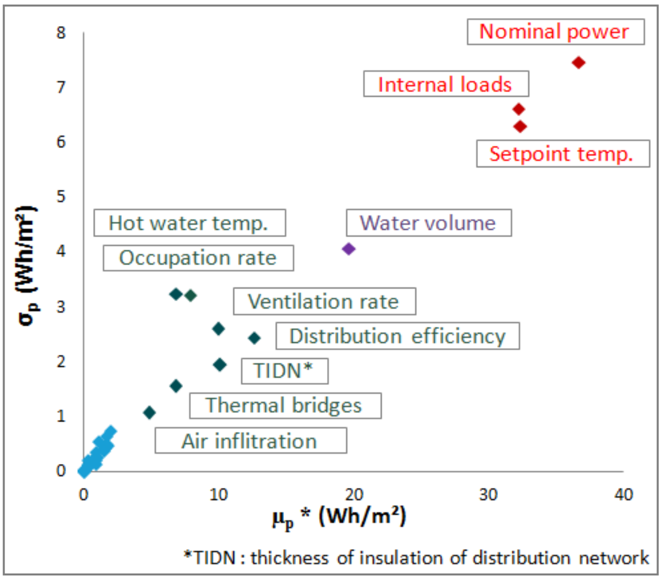

Figure 6: Influential parameters identified using Morris method

PDFs were associated to the influent static parameters in order to run the MC analysis. Concerning occupants' behaviour, the statistical model presented above was used to create a realistic average scenario of presence, internal gains and temperature setpoint, from a generated set of 200 individuals.

The stochastic model was fed with the following specifications: the number of inhabitants in each flat, which was known in the project, and data concerning the building location. Variability was defined around these mean realistic scenarios calibrated with pre-retrofit electricity consumption. Concerning meteorological conditions, the generator of artificial weather data was used in the MC analysis.

Distribution of energy consumption without adjustment

A complete propagation of uncertainty and variability was conducted to explore the statistical variability of post-retrofit energy consumption, taking 9 hours (including the 4 hours of meteorological data generation) for the 6000 simulations. The related distribution had a mean of 107,2 kWh/m².yr and a standard deviation of 16.3 kWh/m².yr. The 95 %-quantile consumption of 134.1 kWh/m².yr exceeds the nominal value by 25 %. The gap between this value and the average consumption highlighted the interest to propose a guarantee with adjustment in an energy performance contract in order to improve forecasting accuracy.

Definition of the adjustment variables

To exclude the influence of parameters which are not related to ESCOs' responsibility, the adjustment of the guaranteed consumption limit (GCL_{α}) thanks to appropriate AVs was anticipated.

A preliminary study investigated the relevance of different sets of AVs focusing on temperature setpoint and outdoor temperature influence on heating energy consumption. We compared the fit of linear regression models relating the heating energy consumption to combinations of different AVs. Several AVs can depict the impact of outdoor temperature:

- The Heating Degree Days with a baseline of 18°C (HDD_{18}) calculated during the heating season. During simulation, we calculated the mean between daily maximal and minimal outdoor temperature. For each day of the heating season (extending from weeks 42 to 18), we added positive differences between the baseline temperature and this value.
- The Heating Degree Hours with a baseline of 18°C calculated during heating season ($HDH_{18\text{-}hs}$). During simulation, we calculated the difference between baseline temperature and hourly outside temperature. The positive hourly differences were added during all heating season. During measurement operation, hourly mean temperatures were considered to calculate $HDH_{18\text{-}hs}$.
- The average outdoor temperature during heating season ($\bar{T}_{out-hs}$).

Other variables can characterise the influence of indoor temperature on heating energy consumption:

- The average indoor temperature during heating season ($\bar{T}_{in-hs}$). Simulations considered that indoor temperature during winter is equal to the temperature setpoint. Indoor temperature was measured during building operation. This variable was calculated for each flat and we considered a global average weighted by surface areas.

Finally, both aspects can be taken into account:

- The Heating Degree Hours with a fluctuating baseline corresponding to indoor temperature ($HDH_{Tin\text{-}hs}$) features impacts of both indoor and outdoor temperatures. These quantities were combined because they are involved in the same physical processes, mainly heat transfer and air leakage. A weighted average of this variable evaluated for each flat was finally calculated.

Different sets of AVs were studied in order to adjust the global heating consumption to indoor and outdoor temperatures. We compared the RMSE of the corresponding multi-linear regressions. Sets and associated results are shown in Table 1.

Table 1: Comparison of the relevance of different adjustment models

Adjustment variables	RMSE (kWh/m².yr)
HDD_{18}	5.0
$\bar{T}_{in-hs}$	6.4
HDD_{18} / $\bar{T}_{in-hs}$	4.6
$HDH_{18\text{-}hs.}$ / $\bar{T}_{in-hs}$	4.4
$\bar{T}_{out-hs}$ / $\bar{T}_{in-hs}$	4.4
$HDH_{Tin\text{-}hs}$	4.2

Results first show that *HDH* performed better than *HDD* depicting more accurately outdoor temperature effects. The unique AV $HDH_{Tin\text{-}hs}$ characterising both inside and outside temperature displays the best predictive performance. Therefore, this AV was selected.

Other AVs were chosen according to available project data. Three AVs composed the intended adjustment model. $HDH_{Tin\text{-}hs}$, describes the influence of both outdoor and indoor temperatures. Global specific electricity consumption during heating season ($E_{elec\text{-}hs}$) characterises the influence of internal gains on heating loads. Annual water volume (V_w) has an effect on both water heating consumption and heating loads, due to energy losses in the water distribution circuit.

Definition and application of M&V procedure

The methodology presented above allowed defining a measurement plan associated to the adjustment model. In this case study, the building was monitored during the first year of operation after retrofit, providing the required data.

A +/- 0.5°C temperature measurement's uncertainty (ΔT) was considered. For each simulation, and for each sensor a random value of systematic error was drawn from a normal distribution with a standard deviation of $\Delta T/2$. The impact of random error was neglected, its effects offsetting each other on the entire study period. The final error on $HDH_{Tin\text{-}hs}$ was calculated as a sum of errors on temperature differences over the heating season. Concerning the annual water volume V_w, we supposed a relative uncertainty $\Delta V_w/V_w$ of +/-5%. It was modelled as a normal distribution with a standard deviation $\Delta V_w/2$. The same process was conducted to set an error on $E_{elec\text{-}hs}$ with a relative uncertainty of +/-2%.

The quantity of interest Y is composed of heating and hot water energy consumption. Energy was measured thanks to a heat meter in the building's substation. The corresponding relative uncertainty was estimated as +/-5%, represented by a normal distribution with a standard deviation of $\Delta Y/2$. Simulated values of the AVs and energy consumption were modified by random draws in their associated PDFs.

Adjustment model determination

We realised a multiple linear regression from the complete MC analysis results accounting for measurement errors. It allows defining the polynomial function relating the mathematical expectation of energy consumption to AVs. We carried out a student test, which confirmed that there is no significant correlation between AVs. AVs' reference values are presented in Table 2.

Table 2: Adjustment variables in reference conditions

Adjustment variables	reference values
$HDH_{Tin\text{-}hs.}(K.h)$	58694
V_{hw} (m^3)	627.8
$E_{elec\text{-}hs}$ (kWh)	11316

Splitting the data set according to AVs values, we study the distribution of deviations from the model. We defined the 95 %-quantile value for each data set by enumeration and deducted the polynomial coefficients of the 5 %-risk adjustment model. Equation (3) shows this final adjustment polynomial formulated as the sum of guaranteed value in reference conditions and weighted growth rates of AVs from reference AVs values.

$$GCL_{5\%} = 122.6 + 77.2 \times \left(\frac{HDH_{18-hs}}{HDH_{18-hs-ref}} - 1\right) -7.7 \times \left(\frac{E_{elec-hs}}{E_{elec-hs-ref}} - 1\right) + 63.6 \times \left(\frac{V_w}{V_{w-ref}} - 1\right) \quad (3)$$

With the adjustment process, the energy consumption uncertainty was decreased as shown in Figure 7. Without adjustment, energy consumption distribution had a large standard deviation of 16,3 kWh/m².yr. Considering adjustment in which AVs were set in reference conditions, the associated standard deviation was 9.6 kWh/m².yr.

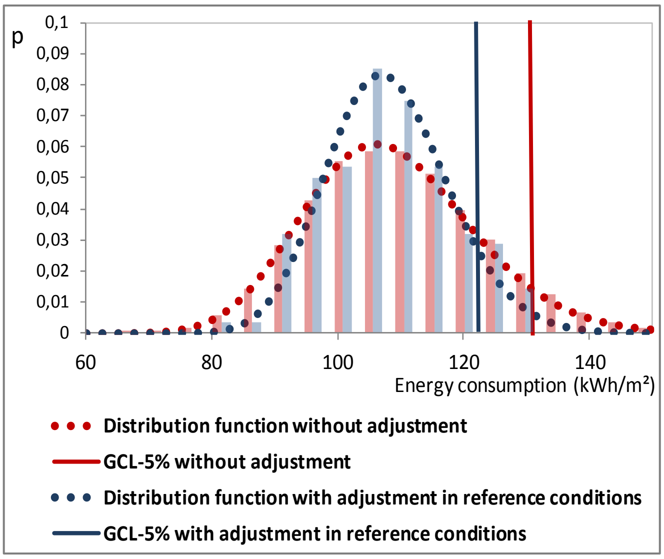

Figure 7: Comparison between distribution functions of energy consumption without adjustment and with adjustment in reference conditions

The adjustment methodology reduced the difference between the guaranteed consumption limit and the reference energy consumption from 25 % to about 15 % higher than the reference consumption for all AV values.

Measurement and Verification process

AVs values were determined from measurements during the first year of operation. They are presented in Table 3 with their associated growth rates relatively to reference values. Outdoor temperature was a bit higher than the reference, but the average temperature setpoint strongly increased after the building retrofit. Thus, HDH_{19-hs} is 9 % larger than the reference value. Water consumption was significantly smaller than expectations, dropping by 30 %. Specific electricity consumption was quite similar to reference values with a slight increase of 6 %.

Table 3: Measured values of adjustment variables and energy consumption during building operation

Adjustment variables	measured values	Growth rates from reference conditions
$HDH_{Tin-hs.}$(°C.h)	64216	+ 9 %
V_{hw} (m³)	441	-30 %
$E_{elec-hs}$ (kWh)	11941	+ 6 %

Energy consumption (kWh/m².yr)	109

Figure 8 shows the consequences of the adjustment process and the comparison between the adjusted $GCL_{5\%}$ and actual energy consumption. Adjusting the AVs according to real conditions, the consumption distribution was shifted and an adjusted $GCL_{5\%}$ was computed. The methodology provided a guaranteed consumption limit of 111 kWh/m².yr with a 5 % risk.

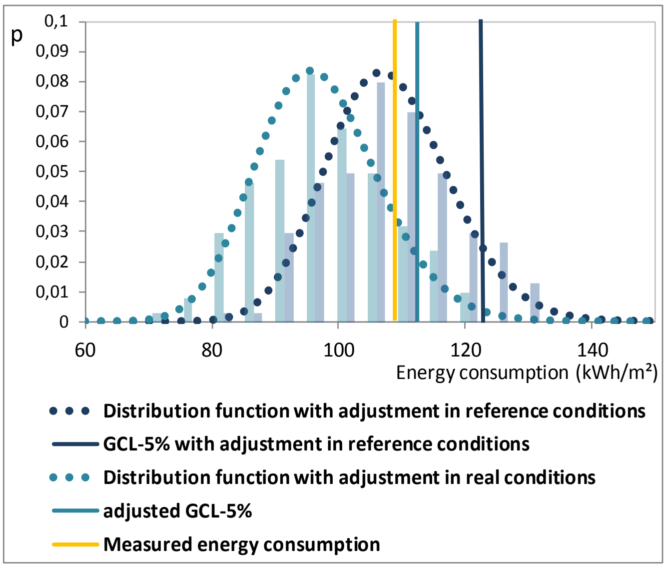

Figure 8: Adjustment of $GCL_{5\%}$ and associated distribution functions of energy consumption. Comparison with actual energy consumption

The large decrease in water consumption was responsible for this reduction of the $GCL_{5\%}$. The monitored energy consumption was 109 kWh/m².yr, lower than the $GCL_{5\%}$ and therefore respecting the performance contract.

Discussion

In this case study, the number of inhabitants post-retrofit was known, allowing the limitation of the generated variability by the stochastic model. Different hypotheses should be considered for a multi-year EPC, anticipating a change in occupancy. The case study includes 16 independent households. The AVs defined in the methodology correspond to average values among these 16 households' behaviour specificities. If only one household is considered (and also in small office buildings), the decrease of the deviation of energy consumption distribution is expected to be more significant.

Conclusion

Typical simulation results of the building considered in the case study provided a unique energy consumption for space heating and domestic hot water of 107.2 kWh/m².yr, considering parameters nominal values and typical scenarios. Carrying out a complete and realistic uncertainty and variability analysis, we noted a large dispersion with a standard deviation of 16,3 and a guaranteed consumption of 134 kWh/m².yr with a 5% risk.

Applying the methodology presented in this article led to a guaranteed consumption limit of 122.6 kWh/m².yr in reference conditions associated to a measurement plan and to an adjustment polynomial. The measured energy consumption during building operation, 109 kWh/m².yr, was lower than the adjusted guaranteed consumption limit in real conditions: 111 kWh/m².yr.

A key point of the method is an exhaustive propagation of uncertainty and variability in dynamic building energy simulations, driven by the available knowledge on building operation future conditions. By simulating a statistical set of possible conditions, we can mine the results and develop a correlation model relating energy consumption to explanatory adjustment variables. Thanks to the specification of the measurement plan, the influence of measurement uncertainties on the risk evaluation was accounted for. A linear adjustment model of the guaranteed consumption limit with a risk α was developed, integrating the dependency on AVs values.

Thus, the methodology provides ESCOs with a science based method to elaborate energy performance contracts with a limited risk. It constitutes a global decision support tool to define the guaranteed performance level and the deployment of required measurement equipment corresponding to an acceptable risk level.

Perspectives

An iterative process could be considered in order to choose the best compromise between the risk level and the complexity of the monitoring, associating a financial risk model, and taking into account financial gains and losses. By coupling these methods, an optimisation could be carried out to jointly define the needed measurement accuracy associated to a cost and the financial risk model. Thus, the proposed methodology can be a key element of financial risk estimation model used by ESCOs or insurance companies.

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