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RISK BASED DECISION MAKING FOR ENERGY RETROFTTING: IMPLEMENTING A FEED-FORWARD STRATEGY IN THE BUILDING DESIGN PROCESS

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ABSTRACT

Buildings tend to use more energy than predicted in their design, also known as the energy performance gap. Uncertainties in energy predictions related to this gap are however, rarely quantified by engineers. This leads to significant project risks in energy retrofitting and performance contracting. A feed-forward energy control strategy is proposed to quantify uncertainties in energy predictions based on field data from realized projects. Results of a case study show that the proposed feed-forward approach, not only quantifies, but also reduces uncertainties in energy predictions. Decision makers state that this leads to more secure and profitable energy efficiency investments, because they get better informed on the significance of project risk, which will help to accelerate the market for energy efficiency investments.

KEY WORDS: performance gap, decision making, uncertainty propagation

1. INTRODUCTION

Over the past decades, the building industry has come aware of a recurring mismatch between design based predicted- and in-use energy consumption of buildings, often referred to as the 'energy performance gap'. Evidence on the magnitude of the gap is adding up fast, suggesting buildings tend to use 1.5 to 2.5 times more energy than predicted in their design phase [1,2]. Causes for this gap arise in all different stages of the building process, from poor assumptions and model inadequacy in the design stage to deviant occupant behaviour in the operational stage [3]. The gap due to poor assumptions in the design stage however, can generally not be redressed or reduced after building completion. This makes improving the predictions even more important in the challenge to reduce the energy performance gap. Therefor this study focusses specifically on the gap that arises in the design stage, by improving the accuracy of predictions on building energy performance.

The fact that the actual energy consumption of buildings can largely deviate from its predicted consumption shows that predictions on energy performance have significant uncertainties. Such energy predictions are however typically given by specific value, a point estimate, suggesting there is no uncertainty at all. This incomplete representation of energy predictions is illustrated in figure 1, showing the given point estimate with the disregarded uncertainty range.

Although most engineers will acknowledge that there is some extend of uncertainty in their predictions, uncertainties are rarely quantified or communicated towards decision makers of energy investments [4]. This can have a large impact on the market of energy conservation investments, especially in case of performance based contracting. For example, a mismatch of 50% in energy performance will turn a sound and profitable

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business-case into a financial loss for an Energy Service Company. But the same also holds for every other conventional energy conservation investment project. In preliminary stages of such projects, when uncertainty is at its highest, uncertain predictions are used as basis for comparison of different energy conservation measures (ECM's) and to decide whether to invest or not. Integrating uncertainty quantification in energy predictions is needed to ensure sound business-cases and accelerate the market of energy conservation investments.

An accurate and often used method for uncertainty quantification is the propagation of probability distributions on input parameters to an output distribution. Since these methods only propagate uncertainty from input to output, particular attention has to be paid to the type of uncertainty distributions assigned on these input parameters. Almost all previous studies on uncertainty quantification in building models emphasize on the lack of proper information on the uncertainty in input parameters [5,6,7]. Improvements have to be made in defining the input distributions for uncertainty quantification, in order to come to an appropriate basis for risk assessment in building energy predictions.

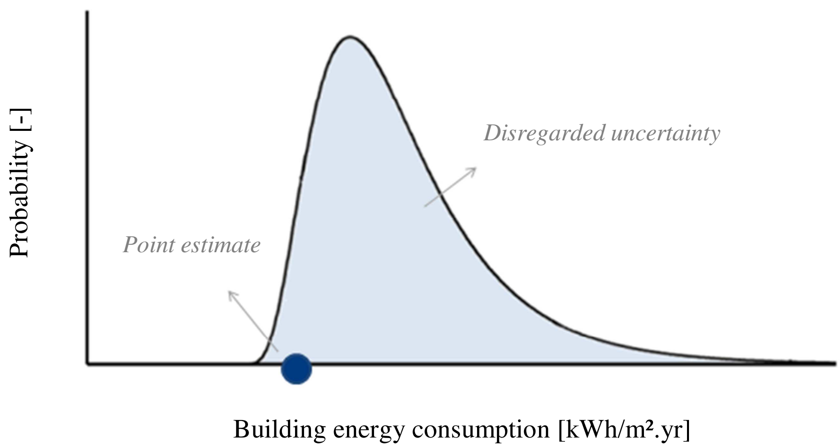

Fig. 1 The incomplete representation of uncertainty in energy performance predictions.

2. METHODOLOGY

To get a better view on uncertainties and narrow the gap in energy performance, a feed-forward strategy is introduced. Continuous performance measurements from completed projects are used as information in a new project, as illustrated in figure 2. The performance measurements can be on KPI's of HVAC components, renewable energy production, building use and many more. All of them parameters that are typically been used as starting points for energy performance predictions. By building up a structured database from field date of these KPI's, a true picture of the energy performance can be obtained of the as-built performance for typical ECM's.

Given that the collected sample data gives a true representation of the typical as-built performance, the distribution of the sample data also gives a true representation of the distribution in as-built performance. To use this sample distribution of KPI's for further computation, each distribution is described by a probability distribution function. Data of each KPI is evaluated on the twenty most common probability functions by using Bayesian Information Criterion and ranked by means of Maximum Likelihood Estimation (MLE) to find the probability function that describes the sample data best. With assigning a probability distribution to each KPI, a realistic view is obtained on the uncertainty in the parameters.

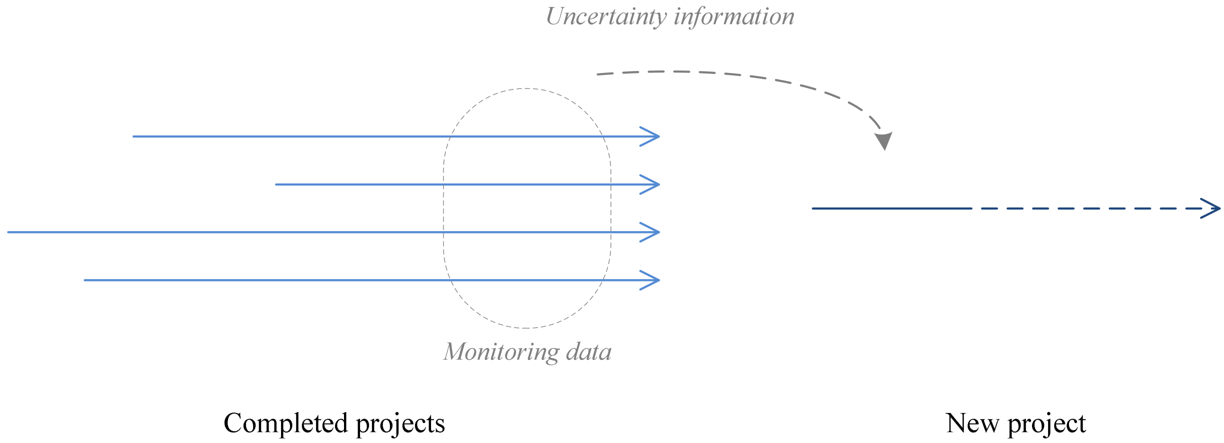

Fig. 2 A schematic representation of the feed-forward strategy.

In order to translate the uncertainty distribution in the typical KPI's to an uncertainty in the final energy performance prediction, a method of uncertainty propagation is needed. In this study Monte Carlo analysis (MCa) is applied. MCa is based on running a simulation a large number of times, each run having a different input setting (sampling based uncertainty propagation). The sampling scheme used for the MCa consists of 1000 samples and is generated by means of Latin Hypercube Sampling (LHS).

3. CASE STUDY

To evaluate practical implementation and the added value of the feed-forward strategy, the method is applied on a case study. As case study the deep retrofit of the main office building of Royal HaskoningDHV is taken. This office building is situated in the centre of the Netherlands, was built in 1970 and houses almost 800 employees on a gross floor area of 19.200 m². The building has had a deep retrofit in 2011, when the office was upgraded from energy label G to A.

The original choices between ECM's were reconsidered in the case study, following the feed-forward strategy. This means that the pre-retrofit building (label G) was taken as base case and energy conservation measures were re-evaluated and reconsidered. Energy savings were projected for each ECM by following the feed-forward strategy. To show the added value of the proposed approach, the ECM's were also simulated following the standard deterministic approach (taking no uncertainties into account). Input for the KPI's in the deterministic approach was determined by conducting an inquiry amongst 12 experienced building services engineers. The monitoring data for the feed-forward strategy was collected from monitoring projects of Royal HaskoningDHV and data from third party field studies. Figure 3 gives an overview of all processing steps within the case study.

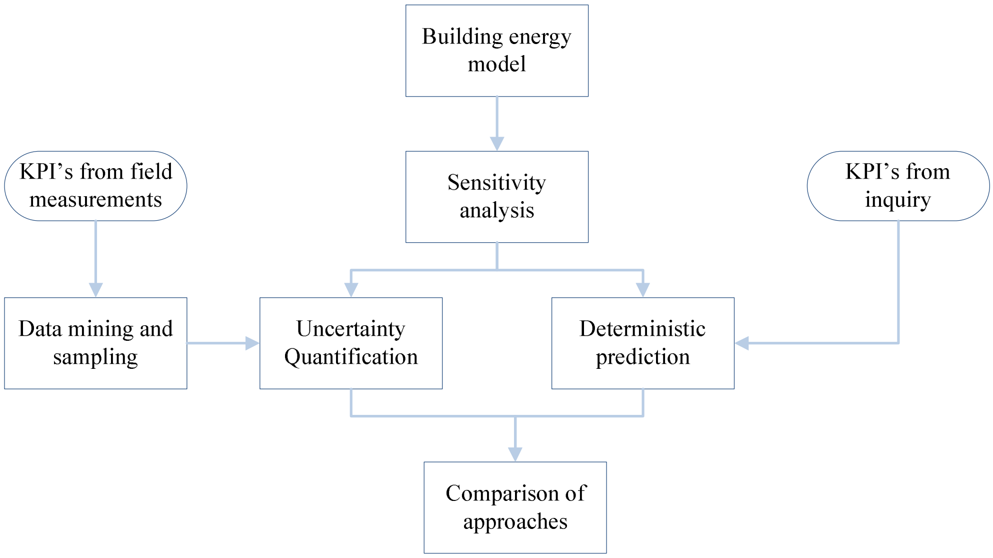

Fig. 3 A schematic overview of all processing steps within the case study.

To limit the computational effort in the study, the feed-forward strategy was applied on a total of four ECM's for the case study. The sensitivity analysis was used to select these ECM's that have a large impact on energy consumption and at the same time were subjected to significant uncertainty. Table 1 shows the four ECM's that were used for the study.

Table 1 Description of the ECM's selected for the case study.

Measure	Description
ECM 1	Replacement of the current power plant by Aquifer Thermal Energy Storage (ATES) combined with a water-source heatpump
ECM 2	Instalment of a rotary Heat Recovery unit in the existing Air Handling Units
ECM 3	Replacement of the current power plant by an air-source heatpump
ECM 4	Combination of ATES and Heat Recovery (ECM 1 and 2)

For each ECM, one or more KPI's were identified that largely affect the projected energy savings of the measure. Field data for the KPI's of ECM 1, 2 and 4 was collected from third party field studies. The KPI for ECM 2 is based on monitoring data from Royal HaskoningDHV, where two air handling units were both continuously monitored for 20 months. Although this sample size is relatively small, the data showed similar patterns as earlier depicted by Grzebielec [8]. An overview of all KPI's with their corresponding sample size and source is given in table 2.

Table 2 Overview of all KPI's used for the case study with their corresponding sample size and data source.

Measure	KPI's	Unit	Sample size	Data source
ECM 1	Seasonal Performance Factor ATES cooling	-	55	Field study [9]
	Seasonal Performance Factor ATES heating	-	53	Field study [9]
	Seasonal Performance Factor heatpump	-	56	Field study [10]
ECM 2	Thermal efficiency	%	2	Monitoring projects
ECM 3	Seasonal Performance Factor heatpump	-	18	Field study [10]
ECM 4	*see ECM 1 and 3*	-	-	-

Besides uncertainty in KPI's of the ECM's, the ECM's were also evaluated on deviations in occupant behaviour. Occupant behaviour is not only a stochastic process, it can also significantly change over time. To account for this change over time, a timespan of 20 years is simulated in which typical indicators for occupant behaviour smoothly change. The sensitivity of the ECM's to this change is evaluated by comparing different scenarios for adaptation in occupant behaviour: worst case, best case and most likely behaviour. Table 3 gives an overview of the settings used for year 1 and year 20 for each scenario, the settings for intermediate years (year 2-19) are linearly interpolated from these numbers.

Table 3 Overview of the settings used to simulate a worst case, best case and most likely scenario for occupant behaviour.

Measure	Unit	Worst case scenario		Most likely scenario		Best case scenario	
		Year 1	Year 20	Year 1	Year 20	Year 1	Year 20
Occupancy rate	%	51	80	48	60	45	30
Plugload intensity	W/m²	16	20	15	15	13	5
Heating setpoint	°C	22	21,5	21	21	20	20,5
Cooling setpoint	°C	23	22,5	24	23,5	25	24

4. RESULTS

The as-built data gathered for the KPI's is used to draw probability functions for the uncertainty. Figure 4 shows the results for one of the KPI's: the Seasonal Performance Factor (SPF) for an ATES system during cooling mode. The bars in the figure show a histogram of the acquired as-built data. The red line in the figure represents the probability density function which is fitted on this data.

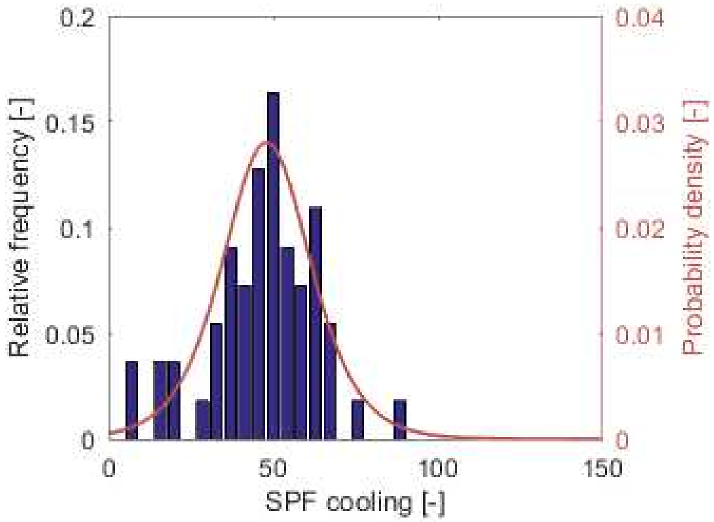

Fig. 4 Histogram plot of the acquired field data (blue columns) and corresponding probability density function (red line) for the SPF-cooling of ATES systems.

With the probability density functions as input parameters, a Monte Carlo analysis was performed to determine the prospected energy savings for each ECM. At the same time the deterministic simulation was performed with the single-number KPI's from the inquiry, based on the results of the inquiry amongst professionals from the industry. Figure 5 shows the results for ECM 1, expressed in savings on Life Cycle Costs (LCC). The savings as predicted by the professionals (boxplot) are significantly higher than would be expected based on measurement data (histogram). The large bandwidth in the boxplot originates from the spread in results of the inquiry (all engineers have different opinion on KPI values). This spread is known as the bias error and appears to be significantly larger than the spread in results of the Monte Carlo analysis.

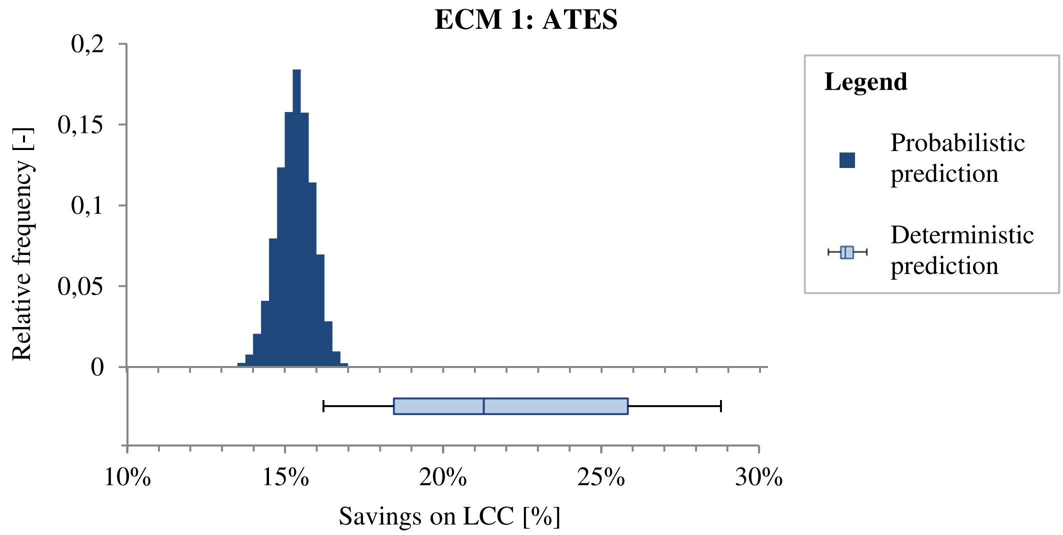

Fig. 5 Comparison of the probabilistic- and deterministic approach for predicting the savings on Life Cycle Costs of an ATES system.

A best- and worst case building use scenario was defined based on extreme parameters for occupancy rate, room temperature set-points and plug-load use. Figure 6 shows the results in energy savings for ECM 1, expressed in simple payback period. The uncertainty in occupant behaviour shows to be of the same order as the uncertainty from the KPI's.

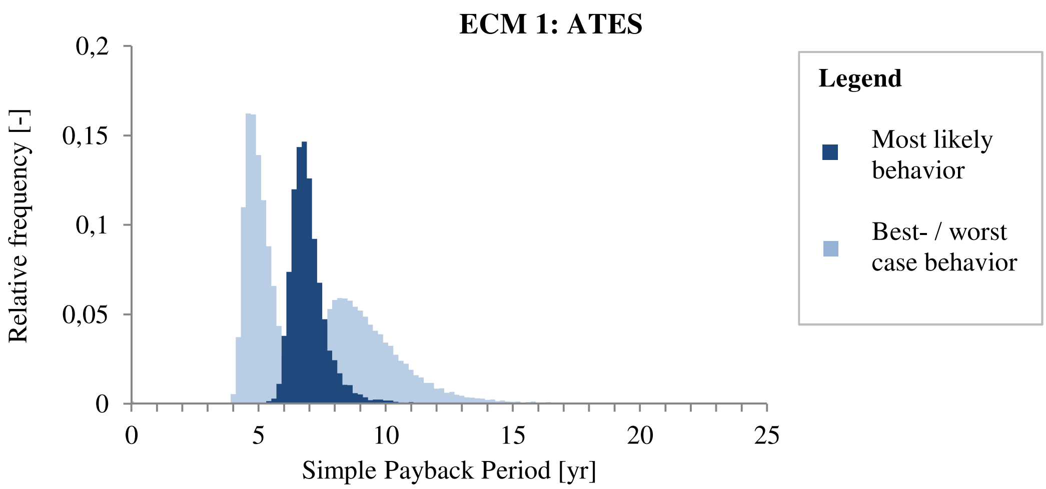

Fig. 6 Predicted Simple Payback Period of an ATES system based on best case, worst case and most likely occupant behavior.

One of the primary advantages of the feed-forward strategy is that it allows more transparency on uncertainties and risks in the communication towards decision makers. Interviews with two leading decision makers working in the Dutch energy investment industry (one technical consultant and one financial consultant), confirmed that the quantification of uncertainties is a necessary step for engineers to increase their credibility. Compared to financial and legal consultants, technical consultants were the only one around the table not familiar with risk based decision making. By communication in terms of risk and return, risks will can be identified more often and earlier the project. This makes mitigation of the risks easier and allows to make better informed decisions. Both consultants stated that a risk-return representation will increase their awareness on potential business-cases and accelerates the market for energy efficiency investments.

5. DISCUSSION

With this study, the added value of the feed-forward strategy has successfully been shown, better informed decisions can be made for energy retrofitting. These obtained results are however only valid for the case building where the feed-forward strategy was applied on, further research on other buildings is therefore recommended. When the proposed method is applied on other buildings it is also recommended to repeat the sensitivity analysis.

The probability density functions of the KPI's were drawn on a limited amount of field-data, varying from 2 to 55 datasets per KPI. Increasing the size and the amount of datasets is needed to increase the accuracy of the probability distributions and will help to improve the energy performance predictions even further.

Profitability of ECM's in this study was expressed in terms of energy savings or LCC. However, most ECM's will also lead to improvements in comfort level and occupants' satisfaction. This improvement can have significant benefits for the building owner or tenant that are not taken into account yet.

6. CONCLUSIONS

The performance gap due to poor assumptions in the design stage of energy efficiency studies can be up to 50%, changing the simple payback time of an ECM up to 100%. Besides the fact that this is a significantly large uncertainty range, these uncertainties have merely negative outcomes, energy savings are consequently overestimated in the deterministic predictions.

Although deterministic energy predictions are often given as precise numbers and point-estimates, they have a large hidden uncertainty due to subjectivity of the engineer (known as the bias error). Results of the case study show that this uncertainty in predictions can be reduced by about 50% with implementation of the feed-forward strategy.

Making energy predictions with the feed-forward strategy allows the engineer to communicate energy efficiency investments in terms of risk and return. This makes it easier to identify and mitigate project risks and increase the credibility of the engineer. Decision makers in energy efficiency investments stated that this will increase the awareness on potential business-cases and accelerate the market for energy efficiency investments.

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