Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 180 (2017) 491 – 501

Procedia Engineering

www.elsevier.com/locate/procedia

International High- Performance Built Environment Conference – A Sustainable Built Environment Conference 2016 Series (SBE16), iHBE 2016

Probabilistic Life Cycle Cost analysis of building energy efficiency measures: selection and characterization of the stochastic inputs through a case study

Elisa Di Giuseppe[a*], Andrea Massi[a], Marco D'Orazio[a]

[a]*Department of Construction Civil Engineering and Architecture, UNIVPM, Via Brecce Bianche 12, Ancona 60131, Italy*

Abstract

In recent years, the boost to the realization of "nearly Zero Energy Buildings" (nZEB) could require so high investment costs which may be not justifiable with the reduced consumptions (and costs) during the use phase. So, even if the estimated potential saving of energy efficiency projects seems to be very high, investors are often discouraged by a high-risk perception, linked to difficulty in knowing the real costs of advanced and innovative technologies, assessing unforeseen costs, or taking into account the significant fluctuations in energy costs. Life Cycle Cost Analysis (LCCA) in buildings could be a useful estimation method, but a large set of input parameters and accurate predictions is required to achieve an effective assessment. Aim of this study is the selection and characterization of the stochastic inputs to be exploited in a probabilistic LCCA to find the cost-optimal energy efficiency measures. We developed a Monte-Carlo based methodology for uncertainty quantification and sensitivity analysis, which combines Global Costs calculation with Building Energy Simulation and we applied it to a building case study, representative of the typical Italian stock. We characterized the stochastic inputs typically involved in the Global Cost method (related to the initial Investment Costs, Annual Costs, Residual Values, and Discount Rates) and analyzed the impact of these parameters on the final results in different renovation scenarios. Results showed that the financial factors (inflation and discount rate) and the energy trend uncertainty are the most influential parameters. Nevertheless, pushing towards nZEB makes it increasingly important the accuracy of investment costs data.

Peer-review under responsibility of the organizing committee iHBE 2016

Keywords: nZEB; LCC; Monte-Carlo; sensitivity analysis; uncertainty analysis

* Corresponding author. Tel.: +39-071-2204380.
E-mail address: e.digiuseppe@univpm.it

Peer-review under responsibility of the organizing committee iHBE 2016
doi:10.1016/j.proeng.2017.04.208

1. Introduction

In the last 50 years the significant changes to the regulatory framework in the context of building energy efficiency have led to substantial reductions in buildings consumptions (and therefore costs during the use phase), even through modest efficiency measures. In recent years, the additional boost to the realization of “nearly Zero Energy Buildings” (nZEB) could instead require so high investment costs which may be not justifiable with the reduced consumptions (and costs) during the use phase. So, even if the estimated potential saving of energy efficiency projects seems to be very high, investors are often discouraged by a high-risk perception, linked to difficulty in knowing the real costs of advanced and innovative technologies, assessing unforeseen costs, or taking into account the significant fluctuations in energy costs that alter the return on investment over time.

Life Cycle Cost Analysis (LCCA) in the field of building construction or renovation is a useful assessment method to compare the effectiveness of different energy efficiency measures (EEMs) and chose the most profitable design options. LCCA provides the total expected costs and benefits (expressed in terms of money) due to the application of an EEM, evaluated during an established time frame and adjusted for the time value of money.

Nevertheless, a large set of input parameters and accurate predictions are required to achieve an effective assessment. Data uncertainty is a well-recognized issue associated with LCC deterministic calculation methods [1–3]. In particular, results are heavily dependent on future trends for economic data and the corresponding uncertainty (e.g. inflation rate and energy prices) or on service life of building components [1,4,5].

If LCC methodologies in the field of buildings are considered as important decision supports, it is then necessary to assess and communicate the problem of uncertainties properly [6]. A probabilistic approach provides more realistic informations about results uncertainty and enables more useful analysis of potential benefits of a design option.

The probabilistic methodology described in this work is based on an uncertainty and sensitivity analysis via Monte Carlo (MC) approaches. They consist of randomly selecting or sampling input variables according to their probabilistic characteristics and inserting them into the output-equation to predict the corresponding output parameters. MC are effective methods used to build the entire output probability density function and to asses global uncertainty and sensitivity [6]. Uncertainty analysis (UA) is the study of the model output distribution as a function of the input parameters’ distribution. Sensitivity analysis (SA) goes one step further by apportioning the output variations to the input variations [7]. While a deterministic analysis approach requires input variables that are fixed, in a probabilistic approach every input parameter is considered as a stochastic variable, modelled using a probability density function (PDF). The quantification of the uncertainty of the output is a result of possible variance of the input parameters.

In this paper we applied MC methods for the probabilistic LCCA of different energy efficiency scenarios for a building case study, representative of the typical Italian stock. We characterized the stochastic inputs typically involved in the Global Cost method established by European Standard EN 15459 [8] (related to the initial Investment Costs, Annual Costs, Residual Values, Discount Rates) and we analyzed the impact of these parameters on the final result in different renovation scenarios.

Nomenclature

C	cost	[€]	L	lifespan	[years]
η	efficiency	[-]	R	rate	[-]
t	time	[years]	U	thermal transmittance	[W/m^{2}K]
Val	value	[€]	F	factor	[-]

Subscripts

a	annual	disc	discount
env	envelope	e	evolution (rate)

F	final	f	floor
g	global	gn	generation
I	investment	i	inflation
int	interest	M	maintenance
pv	present value	R	real interest
w	window		

2. Methodology

The work can be summarized by the following phases, further described in the paragraphs below:

- Selection of a building case study, definition of several energy efficiency measures and related costs;
- Selection and characterization of the stochastic inputs through Probability Density Functions (PDFs);
- Development of a Monte-Carlo based tools suite for the uncertainty and sensitivity analysis.

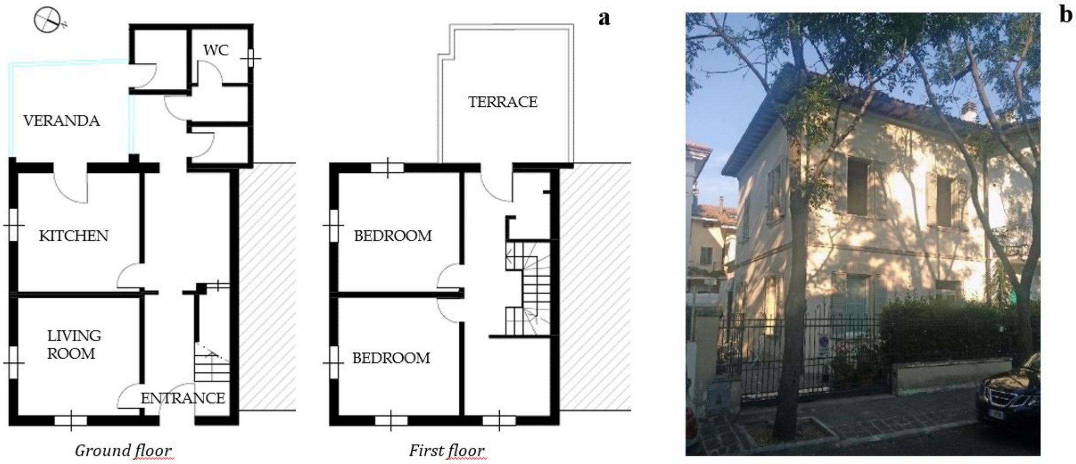

Fig. 1. (a) Building plans; (b) View of the north facade.

2.1. Building case-study and Energy Efficiency Measures

The case study is a single-family detached house with two floors and an attic of early '900, located in Cattolica (average heating degree days: 2165), a coastal town in the centre of Italy (Fig. 1). The gross volume of the building is about 467 m^3, the net floor area 178 m^2, for a surface/volume ratio of 0.82. The original walls are made by plastered brick masonry (29 cm thickness, U=1.76 W/m^2K), while floors and roof consist on wood slabs with respectively pavements (U=1.29 W/m^2K) or clay tiles (U=1.68 W/m^2K). Original windows have timber frames and a 4 mm single glazing (U=5.7 W/m^2K). The heating system consists on a conventional natural gas boiler (23 kW peak power) and radiators.

Four renovation scenarios have been selected based on the Italian regulations on the energy efficiency in buildings that followed one another over the last 15 years. The scenarios includes different EEMs mainly concerning the reduction of the envelope thermal transmittance and the heating equipment efficiency (Table 1).

Table 1. Energy Efficiency Measures related to the four Scenarios identified for the building case study.

Measure	Unit		Scenario 0	Scenario 1	Scenario 2	Scenario 3
Building Envelope – External Wall	U_{env}	[W/m^{2}K]	0.48	0.34	0.30	0.26
	C_I	[€/m$^2_{env}$]	44.62	54.52	58.48	62.44
	C_M	[€/m$^2_{env}$/y]	0.90	0.90	0.90	0.90
	L	[years]	50	50	50	50
Windows	U_w	[W/m^{2}K]	2.8	2.2	1.9	1.4
	C_I	[€/m^2_w]	250	380	400	435
	C_M	[€/m^2_w/y]	7.50	7.50	4.35	4.35
	L	[years]	30	30	30	30
Heating system	η_{gn}	[-]	0.868	0.898	0.918	0.918
	C_I	[€/m^2_f]	14.60	15.70	19.10	65.20
	C_M	[€/m^2_f/y]	0.30	0.32	0.38	1.30
	L	[years]	20	20	20	20

2.2. Global cost calculation method and definition of the PDFs of the stochastic inputs

The evaluation of the cost-benefits of the EEMs in the four scenarios has been carried out based on the Global Cost method described in the European Standard EN 15459 [8]. The global costs $C_g(t)$ referred to the starting year t_0 are calculated by summing, for each component j, the initial investment costs C_I, the annual costs C_a discounted by the rate $R_{disc}(i)$ for every year i and the residual value Val_F, as shown in Eq.(1).

$$C_g(t) = C_I + \sum_j \left[\sum_{i=1}^{t} \left(C_{a,i}(j) \cdot R_{disc}(i) \right) - Val_{F,t}(j) \right] \tag{1}$$

The initial investment cost C_I represents the construction/installation cost of the EEM considered. The annual costs C_a include recurrent costs such as components maintenance costs and energy carriers' costs. The replacement costs of components are to be considered in recurrent costs too, but with a frequency depending on the lifespan of the j component concerned. Finally, the residual value Val_F is calculated based on a straight-line depreciation of the initial investment or replacement cost of the component until the end of the calculation, discounted at the beginning of the evaluation period.

As the main objective of the evaluation is the comparison of different efficiency scenarios, the only investment cost items included in the LCC evaluation are those relating to the EEMs. The following cost items are therefore omitted from the calculation: the costs related to building elements that have no influence on the energy performance, and the costs that are the same for all the measures. The global cost is directly linked to the duration of the calculation period t, that has been considered of 30 years, as established by the European Commission Delegated Regulation and its Guidelines [9,10] for residential buildings.

In order to lead the global costs calculation in probabilistic terms and perform the Monte Carlo simulation, to the following LCC input variables a PDF has been assigned, based on literature data and authors' judgment: (1) Inflation rate R_i, (2) Interest rate R_{int}, (3) Energy prices evolution rate R_e, (4) Component costs C_I, (5) Maintenance costs C_M.

Inflation rate and interest rate affect the real interest rate R_R, according to Eq. (2):

$$R_R = \frac{R_{\text{int}} - R_i}{1 + R_i / 100} \tag{2}$$

The real interest rate R_R is used to calculate $R_{disc}(i)$ through the following Eq.(3).

$$R_{disc}(i) = \left(\frac{1}{1 + R_R / 100} \right)^i \tag{3}$$

Finally, in order to take into account the fact that the price development for energy may differ from the inflation rate, a specific present value factor f_{pv} for this price has been introduced in the calculation. It represents a factor by which the energy annual costs are to be multiplied in order to be referred to the starting year. f_{pv} is related to the evolution of the energy prices R_e by the following Eq.(4), where n is the number of calculated years.

$$f_{pv} = \frac{(1+R_e)}{(R_R - R_e)} \left[1 - \left(\frac{(1+R_e)}{(1+R_R)} \right)^n \right] \tag{4}$$

The stochastic character of the macroeconomic parameters depends on the extreme uncertainty of the financial market, whose future evolution is difficult to be exactly predicted. For this assessment, we considered a "baseline" scenario, based on the analysis of time series of these parameters during last years. In particular, for the inflation rate we obtained a normal distribution from fitting the inflation rate time series in Italy, in the period from the adoption of euro currency, when European Central Bank started its monetary policies that aim to maintain the inflation rates below but close to 2% over the medium term. For the interest rate a triangular distribution has been selected with a median value of 4.09%, coming from Bank of Italy survey on personal loans rates. The minimum value was based on the EURIRS 30 years average rate and the maximum rate is the usury limit in Italy. For the energy prices trend and its uncertainty we referred to the Annual Energy Outlook 2015's projections until 2040 of the EIA/DOE [11].

Table 2. Uncertain LCC input parameters.

Parameter	**Unit**	**Standard value**	**Reference for standard value**	**Distribution***	**Reference for distribution**
Inflation rate	[-]	1.9 %	ECB	Nor(0.019,0.010946)	Time series data fitting
Interest rate	[-]	4.09 %	Market analysis (mean)	Tri(0.0149,0.0908,0.0409)	EURIRS/Banca d'Italia
Energy price evolution	[-]	1.59%	EIA/DOE	Nor(0.0159, 0.014037)	EIA/DOE
Components costs	[€]	μ_{cost}	DEI pricelist, Regional pricelists	Uni(μ_{cost} -10%, μ_{cost} +10%)	Pricelists inequalities
Components lifespans	[years]	μ_{life}	EN15459/INIES/ASHRAE	Uni(μ_{cost} -20%, μ_{cost} +20%)	ISO 15686
Maintenance costs	[€]	μ_{maint}	EN15459/Market analysis/Literature	Nor(μ_{maint}, μ_{maint} *3%)	Labour costs inequalities

*Uni($\boldsymbol{a}$,$\boldsymbol{b}$): uniform distribution between $\boldsymbol{a}$ and $\boldsymbol{b}$.
Nor($\boldsymbol{\mu}$,$\boldsymbol{\sigma}$): normal distribution with mean value $\boldsymbol{\mu}$ and standard deviation $\boldsymbol{\sigma}$.
Tri($\boldsymbol{a}$,$\boldsymbol{b}$,$\boldsymbol{c}$): triangular distribution with lower limit $\boldsymbol{a}$, upper limit $\boldsymbol{b}$ and mode $\boldsymbol{c}$, where $\boldsymbol{a} < \boldsymbol{b}$ and $\boldsymbol{a} \leqslant \boldsymbol{c} \leqslant \boldsymbol{b}$.

The initial investment costs were determined through the analysis of regional and national pricing lists for public works. The surveys carried out on prices lead to a prices variation on a geographical basis of about 10%. This uncertainty interval has been considered representative of the price variations that could affect a design choice because of an unforeseen during the design/execution of the work. Therefore it was decided to attribute a uniform distribution (±10%) to the component costs.

The costs of component maintenance were assumed based on market surveys (for the opaque envelopes), literature [12] (for windows), and *Annex A* of EN 15459 [8] (for the heating system components). A normal distribution with 3% standard deviation has been considered.

Finally, data on components lifespans came from *INIES* database [13], *ASHRAE: Service Life and Maintenance Cost Database* [14] and *Annex A* of EN 15459 [8], and are 50 years for the insulation systems, 30 years for window elements and 20 years for system components. To the lifespan uncertainty a uniform distribution (±20%) has been attributed. Table 2 summarizes the uncertain inputs considered in the calculation of global costs and related PDFs.

2.3. Monte-Carlo based methodology for uncertainty quantification

For the purpose of the research, a Monte-Carlo based methodology for uncertainty quantification has been developed, which combines Global Costs calculation with Building Energy Simulation (necessary to obtain the running costs linked to the building energy consumptions). The methodology has been implemented in a tools suite (Fig.2). SimLab software [15] has been used to define the PDFs of the uncertain input parameters. With Latin Hypercube Sampling method, samples with different sizes have been generated and simulations were run with an increasing number of iterations (10, 25, 50, 100, 250, 500, 1000, 2500, 5000). The quality of the related outcome (the PDF of the output sample) has been compared with a reference simulation of 20000 runs.

EnergyPlus software was used for the building energy simulation and the global cost calculation. Life Cycle Cost computation in EnergyPlus is mainly based on NIST Handbook 135 [16], so the original software source code has been modified in order to make it entirely conforming to EN 15459 [8] global cost method, particularly allowing for the automatic calculation of residual values Val_F. Finally, SimLab performed the uncertainty and sensitivity analysis on the outputs.

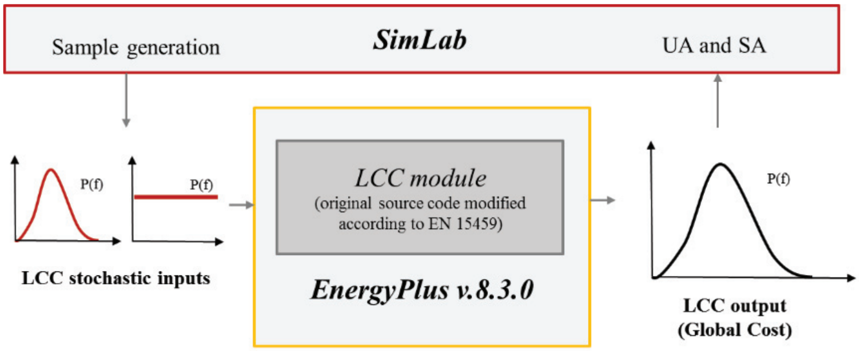

Fig. 2. Diagram of the tools suite for the MC based methodology.

3. Results

To assess whether the number of simulation runs was sufficient to guarantee the quality of the outcome (the PDF of the output sample), the convergence of the mean and standard deviation of the different output samples has been investigated, compared to the reference simulation of 20000 iterations. From Table 3 it is possible to observe the results in terms of mean and standard deviation, and normalized mean and standard deviation (ratio with the reference simulation). A good convergence of the output sample is obtained at 2500 iterations. That is reflected by a quite accurate PDF of the output (Fig.3).

Then goodness-of-fit plots (density, cumulative density function (CDF), Q-Q plot and P-P plot) for global cost output data have been performed (Fig. 4) in order to find the theoretical distribution that better represents the trend of output data (lognormal distribution). Table 4 reports the estimated mean, standard deviation, skewness and kurtosis for the two extreme scenarios (0 and 3).

Fig. 5. represents the PDF and CDF of the global costs (2500 iterations), for the two extreme scenarios (0 and 3). A difference of less than 10000 € in the median value of costs can be observed. In order to evaluate the influence of input data uncertainty on the results (which provides informations about the relative sensitivity of the parameters), Spearman coefficients have been calculated. They are reported in Fig. 6 for scenarios 0 and 3. Macroeconomic inputs as inflation rate, interest rate, energy prices evolution rate are the most influential parameters in both scenarios, even if energy prices escalation is mainly influencing the uncertainty of the result in scenario 0, due to the higher energy consumptions during building use phase. On the contrary, the uncertainties on life times of the components (which determine the replacement costs during the building life time) have greater relevance in the more efficient building (where the energy consumption counts less).

Table 3. Mean, STD, Normalized Mean and Normalizes STD for Global Cost of the case study for each sample size

Number of simulations	Mean	STD	Norm. mean	Norm. STD
20000 (Reference)	68693.83	13336.14	-	-
10	69505.06	16423.78	0.011809296	0.231524089
25	68881.45	13734.42	0.002731233	0.029865030
50	68585.38	11728.32	0.00157874	0.120560984
100	68912.00	13859.22	0.003175909	0.039222883
250	68292.40	12687.16	0.005843767	0.048663440
500	68449.11	12778.93	0.003562475	0.041781892
1000	68545.37	12830.10	0.002161299	0.037945249
2500	68640.88	13244.44	0.000770911	0.006875938
5000	68764.19	13575.97	0.001024265	0.017983349

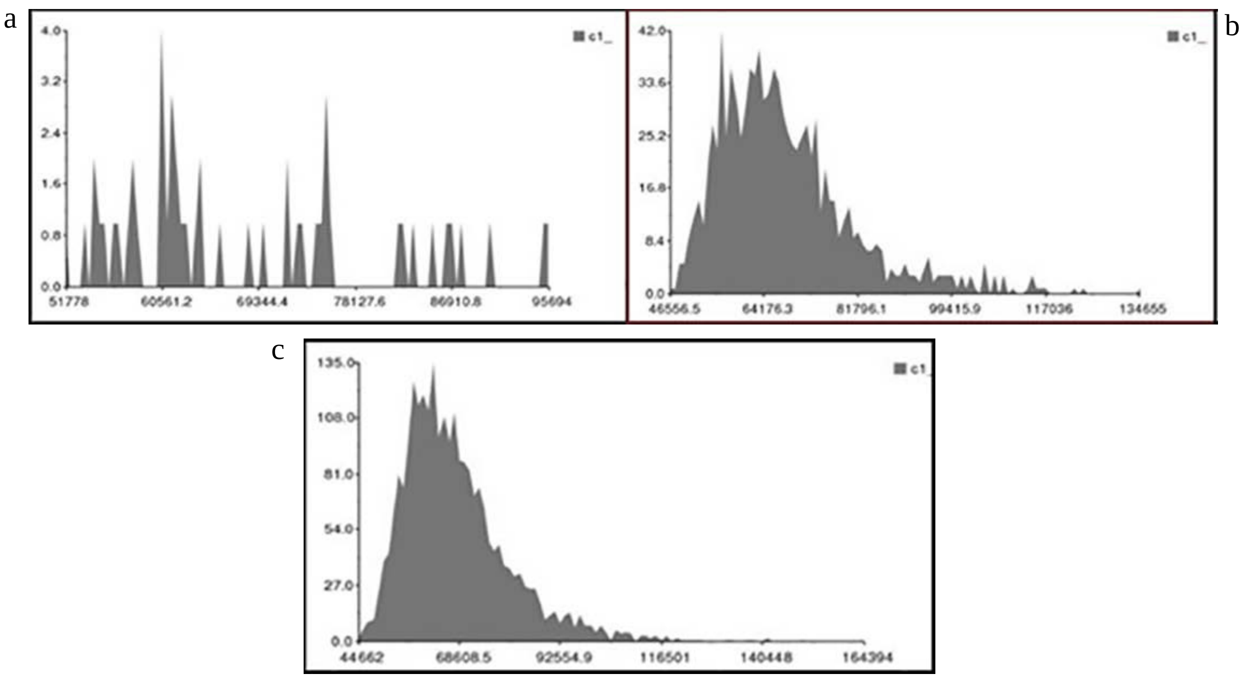

Fig. 3. Output uncertainty analysis for 100 (a), 500 (b) and 2500 (c) sample size.

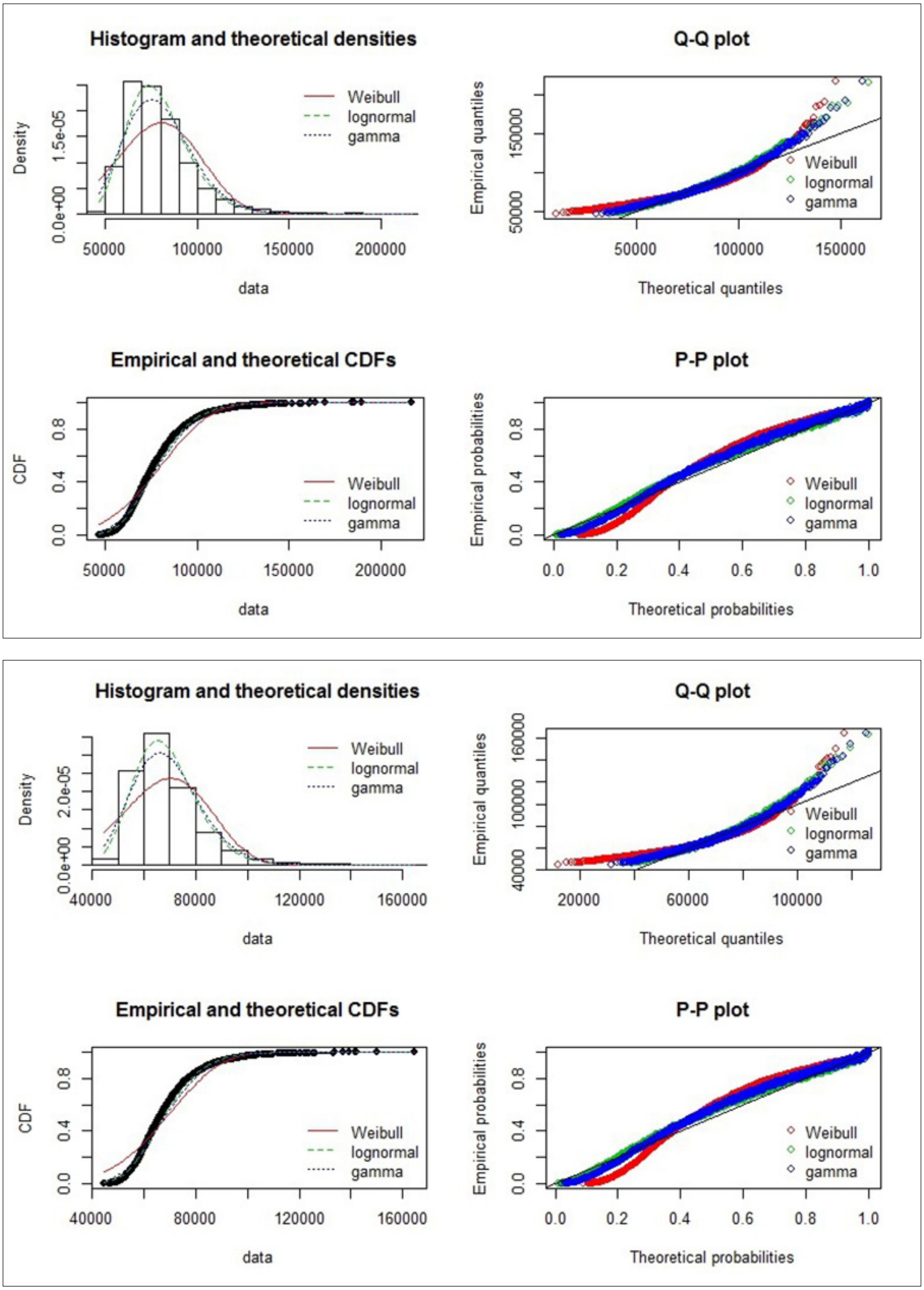

Fig. 4. Goodness-of-fit plots (density, Q-Q plıt and P-P plot) for global cost output data of Scenario 0 and Scenario 3.

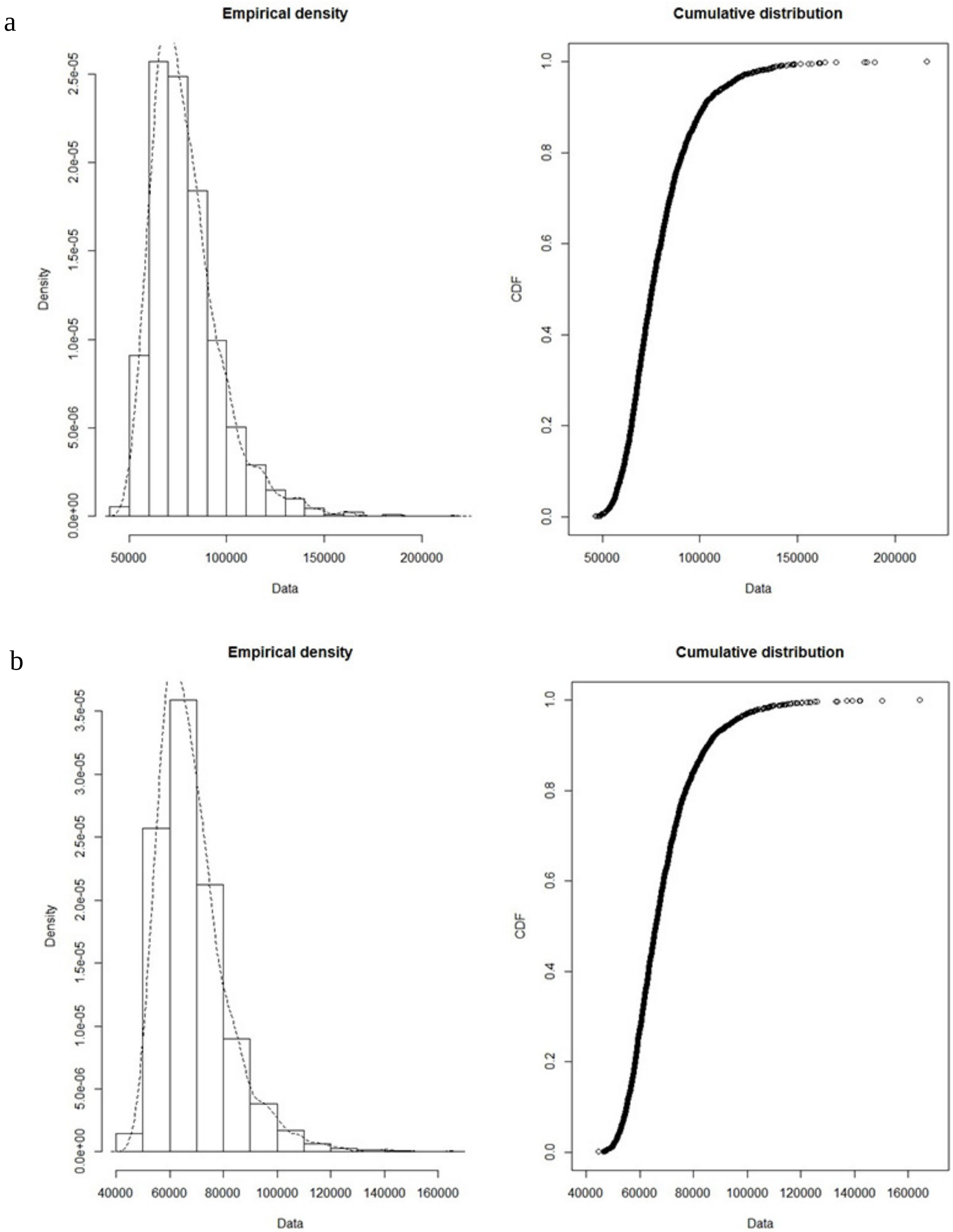

Fig. 5. Density and CDF plots of global cost output for Scenario 0 and Scenario 3.

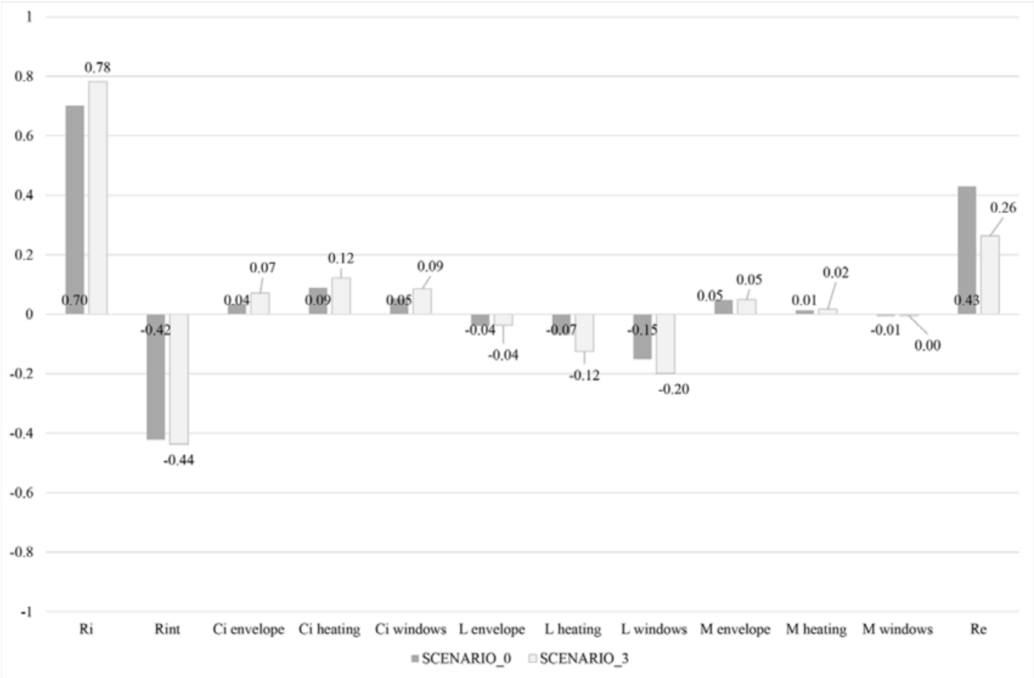

Fig. 6. Spearman Coefficients in Scenario 0 and Scenario 3.

Conclusions

Life Cycle Cost Analysis in the field of building construction or renovation are useful decision methods to compare the effectiveness of different energy efficiency measures and chose the most profitable design option. Nevertheless, a large set of input parameters and accurate predictions is required to achieve an effective assessment and data uncertainty is a well-recognized issue associated with LCC deterministic calculation methods. Probabilistic LCC methodologies could provide powerful decision support for undertaking building energy efficiency measures. Nevertheless, their development in the field of LCC is still at the beginning.

This paper proposed a Monte Carlo based methodology for uncertainty quantification that combines building simulation and Life Cycle Costs analysis and applied it to different renovation scenarios of a building case study. The methodology showed a great potential in undertaking the output uncertainty calculation with low computational costs and high accuracy of the result.

We characterized the stochastic inputs typically involved in the Global Cost calculation method and analyzed through sensitivity analysis (Spearman coefficients) the impact of these parameters on the results uncertainty. Results revealed that macroeconomic inputs, as inflation rate, interest rate, energy prices evolution rate, are the most influential parameters, so they should be further investigated in future studies. In particular future assessments could consider different alternative macroeconomic scenarios where macroeconomic variables are interdependent. Scenarios could then express possible combinations of these variables that can be encountered under different economic conditions and medium and long-term growth patterns. As the event of an economy falling in one of these conditions is largely unpredictable, the choice among scenarios should be driven by other orders of arguments: political relevance, ethical concerns, attitude towards risk, etc.

References

[1] S. Burhenne, O. Tsvetkova, D. Jacob, G.P. Henze, A. Wagner, Uncertainty quantification for combined building performance and cost-benefit analyses, Build Environ. 62 (2013) 143–154.
[2] P. Das, L. Van Gelder, H. Janssen, S. Roels, Designing uncertain optimization schemes for the economic assessment of stock energy-efficiency measures, J Build Perform Simul. 1493 (2015) 1–14.
[3] N. Wang, Y.C. Chang, A. El-Sheikh, Monte Carlo simulation approach to life cycle cost management, Struct Infrastruct Eng. 8 (2012) 739–746.
[4] D. Pittenger, D. Gransberg, M. Zaman, C. Riemer, Stochastic Life-Cycle Cost Analysis for Pavement Preservation Treatments. Transp Res Rec J Transp Res Board. 2292 (2012) 45–51.
[5] S. Rahman, D.J. Vanier, Life cycle cost analysis as a decision support tool for managing municipal infrastructure. CIB Trienn Congr. 2004.
[6] H. Janssen, S. Roels, L. Van Gelder, P. Das, Annex 55 Reliability of Energy Efficient Building Retrofitting. Probability Assessment of Performance and Cost. Probabilistic Tools. International Energy Agency. 2015.
[7] A. Saltelli, M. Ratto, T. Andres, et al.. Global Sensitivity Analysis: The Primer. Wiley 2008.
[8] EN 15459:2007 Energy performance of buildings - Economic evaluation procedure for energy systems in buildings.
[9] Commission Delegated Regulation (EU) No 244/2012 of 16 January 2012 supplementing Directive 2010/31/EU of the European Parliament and of the Council.
[10] Guidelines accompanying Commission Delegated Regulation (EU) No 244/2012 of 16 January 2012 supplementing Directive 2010/31/EU of the European Parliament and of the Council.
[11] U.S. Energy Information Administration. Annual Energy Outlook 2015 with projections to 2040. 2015.
[12] G. Han, J. Srebric, E. Enache-Pommer, Variability of optimal solutions for building components based on comprehensive life cycle cost analysis, Energy Build. 79 (2014) 223–231.
[13] INIES - Les données environnementales et sanitaires de référence pour le bâtiment [http://www.inies.fr/produits-de-construction/]. Last access 16/06/2016.
[14] ASHRAE: Service Life and Maintenance Cost Database [http://xp20.ashrae.org/publicdatabase/]. Last access 16/06/2016.
[15] SimLab [https://ec.europa.eu/jrc/en/samo/simlab]. Last access 16/06/2016.
[16] S.K. Fuller, S.R. Petersen, Life Costing Manual for the Federal Energy Management Program. NIST Handbook 135, 1996.