Investigations of Building-Related LCC Sensitivity of a Cost-Effective Renovation Package by One-at-a-Time and Monte Carlo Parameter Variation Methods

Antonov, Yovko Ivanov; Jønsson, Kim Trangbæk; Heiselberg, Per; Pomianowski, Michal Zbigniew

Published in:
Applied Sciences (Switzerland)

DOI (link to publication from Publisher):
10.3390/app12199817

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

applied sciences

Article

Investigations of Building-Related LCC Sensitivity of a Cost-Effective Renovation Package by One-at-a-Time and Monte Carlo Parameter Variation Methods

Yovko Ivanov Antonov *, Kim Trangbæk Jønsson, Per Heiselberg and Michal Zbigniew Pomianowski

Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, 9220 Aalborg, Denmark
* Correspondence: yovko.antonov@gmail.com; Tel.: +45-22-82-37-44

Abstract: Nearly Zero Energy Building (NZEB) is becoming a standard for new and renovated buildings throughout the European Union (EU). Through the ongoing implementation of directives related to energy efficiency and NZEB-compliant buildings, the EU commission has established that new and renovated NZEB-compliant buildings shall be implemented cost-effectively. This is assessed by linking the Life Cycle Cost (LCC) and energy demand calculations, representing them in a cost-optimality plot, and finding the optimal solution from the resulting Pareto front. Given that the results of an LCC calculation are quite dependent on the calculation model's scope and inputs, this study takes an explorative approach to determine the most influential parameters in LCC calculations for a pre-selected cost-effective package. This is achieved by varying the inputs using local and global variation methods. The local variation approach consists of varying the inputs one-at-a-time (OAT), whereas with global variation, all the selected inputs are variated simultaneously. The OAT approach identified the amount and unit cost of the utility supply (district heating, electricity, and gas) as the most influential parameters to the output. The OAT results were further used to rank the next five most sensitive parameters and perform a global sensitivity analysis using Monte Carlo (MC) simulations. A regression analysis of the MC results revealed high R2 values ($\geq$0.98), suggesting a linear correlation between the output and the variable inputs. The sensitivity analysis determined the unit price of attic insulation, the gas price, and the lifetime of the Heat Pump (HP) as the most sensitive parameters in the three investigated models.

Keywords: LCC; NZEB renovation; robustness; LCC sensitivity

check for updates

Citation: Antonov, Y.I.; Jønsson, K.T.; Heiselberg, P.; Pomianowski, M.Z. Investigations of Building-Related LCC Sensitivity of a Cost-Effective Renovation Package by One-at-a-Time and Monte Carlo Parameter Variation Methods. *Appl. Sci.* **2022**, *12*, 9817. https://doi.org/10.3390/app12199817

Academic Editors: José Manuel Salmerón Lissén and Francisco José Sanchez de la Flor

Received: 28 September 2021
Accepted: 19 September 2022
Published: 29 September 2022

1. Introduction

For the last decade, buildings have become a strategic focus of European policies, namely, the Energy Efficiency Directive (EED) [1] and Energy Performance of Building Directive (EPBD) [2], which aim towards nearly Zero Energy Buildings (NZEBs) and energy efficiency at the European level. Member States of the European Union (EU) are to develop national, long-term renovation strategies for the cost-effective conversion of existing buildings to reach NZEB [2]. Article 2a (b) of Directive 2018/844 [2] further obligates the Member States to establish cost-effective approaches to renovation with respect to the building type, location, and potential trigger points during the lifecycle of the building.

In Denmark, for example, this is well-reflected in a new, voluntary sustainability building class [3]. The new Danish classification includes social, environmental, and economic sustainability criteria. Among other evaluation criteria, the economic category is expressed by the Life Cycle Cost (LCC) [4]. Besides that, the LCC is planned to be mandatory in Denmark, and it has been widely applied to determine cost-optimal minimal energy demands and to seek cost-optimal renovation strategies in multiple publications related to cost optimality for building design and renovations [5–8]. The LCC methodologies are broadly used to forecast expected costs and monetary benefits related to the application of energy efficiency measures (EEM) for energy renovation projects taking into account the time frame and time value of money. The value of the LCC is reflected by finding its place in the regulatory level [2,3] and normative approach for calculation [9], which is further elaborated in Section 2.1 of this paper.

The reliability of cost analysis is inherently dependent on the quality of the input data; thus, the uncertainty analysis of the input is a necessary step in order to consider the LCC of building energy renovation projects as a trustworthy decision support tool [10]. The authors also point also out that a deterministic approach to LCC analysis is heavily dependent on uncertainty, as the input data are fixed in both time and cost. Alternatively, when applying the probabilistic approach, the input variables are modelled using probability distribution functions (PDF); thereafter, the quantification of the output's uncertainty is a result of the sensitivity analysis of the variance of the input parameters. Moreover, even though the deterministic approach could be considered less complex compared to the probabilistic one, it can result in a subjective solution, or one based on faulty assumptions [11]. The probabilistic approach aims to add "robustness" [12] to the solution, but the limiting factor can be a very large number of input parameters (a lengthy process), uncertain distributions, or inefficient sampling.

Probabilistic design exploration methods are well-established when it comes to energy demand calculations, and their strengths, weaknesses, and computational aspects have been comprehensively analyzed and discussed [13–16]. As indicated in [13], the required detail level of the modelling depends on the design phase, where the extent of the sensitivity analysis is bound by the knowledge of the design parameters. The more advanced the design phase is, the more detailed the models used should be. As stated in [14], a sensitivity analysis involves a large number of simulation runs, often applying dynamic building simulation programs. However, to save computational time and lessen input variation, simplified models are usually chosen. Here, the check for the validity of the model is always recommended and often researched in studies, either by comparison of the modelling output results with measurements [17], or by the validation of simpler, steady-state or quasi steady-state models against more detailed dynamic models, as in [18].

When it comes to the sensitivity of renovation-related LCC analysis, the commonly investigated inputs are those related to financial assumptions such as the interest rate and the energy price- and development. For instance, the impact of the energy price on a cost-optimal solution, found by the decision support scheme, is presented in [19]. A sensitivity study on the interest rate and energy price development for newly constructed single- and multi-family NZEB buildings in Greece is presented in [20,21]. The sensitivity of the same two parameters is also investigated in [22] for listed and non-listed multi-family buildings in Sweden located in different climatic zones. In addition to interest rate and energy price development, Ferreira et al. [5] further include energy price as a parameter.

While the sensitivity of building-related LCC calculations is often investigated, the applied method, scope, and detail level of the analysis vary considerably. The uncertainty of seven energy-related inputs with respect to the LCC calculation is investigated in [23] for two scenarios, using the one-at-a-time (OAT) method. The focus of [24] is limited to financial assumptions, yet it applies an optimization-based scheme to investigate many scenarios for a single-family house in Norway, including energy-saving measures, renewable energy sources, and systems. Another example of optimization-based schemes employing solution space exploration is presented in [25]. Such multi-objective optimizations are robust, as the considered parameters' sensitivity is integrated into the method itself. However, a drawback of such methods is that these can be very time and expertise-demanding and implicated by practicalities. There are also studies focusing on how a specific aspect of a renovation affects cost-optimal solutions. For instance, [8] investigates occupant behavior, window-opening activities, and their influence on cost-optimality. Nonetheless, the interest rate, energy prices, and their expected developments seem to be in focus when it comes to sensitivity in the LCC.

Moreover, sensitivity analysis seems to be a secondary objective in research related to cost-optimal solutions, where a common main objective is the selection of an optimal package. For instance, the authors of [6] propose several combinations of EEM to obtain a cost-efficient retrofitting solution for school buildings, while performing a sensitivity analysis that disregards investment costs and focuses only on the interest rates and the increase in electricity prices. Another interesting study [18] presents a sensitivity study by indicating how different input parameters influence the resulting cost-optimal renovation of a multifamily building. The proposed sensitivity accounts for a wide spectrum of input parameters, such as the thermal properties of the building envelope, district heating prices, operation costs, the price increase in district heating, the cost of EEM, ventilation heat recovery, and the discount rate. The applied method varies only one parameter at a time, making it unable to detect the combined effect of input parameters on the output, but obtaining multiple parallel sensitivity analyses [18]. Another comprehensive study proposes a holistic process for determining a cost-effective renovation that could support building energy certification and increase renovation rates [26]. The proposed procedure is composed of three steps, where the final step incorporates the LCC and the renovation plan. The weight of each considered parameter is analyzed to identify the most impactful ones on the energy demand decrease. The method further accounts for the cost and lifetime of each EEM, but in a simplified manner, where the cost of each intervention is split into conservative, medium, and ambitious. The sensitivity analysis in this case disregards the financial parameters, energy prices, the lifespan, variable, and maintenance costs.

To the authors' best knowledge at the time of writing, only study [27] performs an uncertainty characterization on 18 LCC input parameters. The study applies a probabilistic methodology employing Sobol sampling combined with the Monte Carlo (MC) approach. The convergence criteria are used to assess the sensitivity in a calculation concerning a single-family house in Italy. The case applies special economic consequences (penalties) for a reduced usable floor area due to an internal insulation with vacuum panels.

As mentioned above, while most of the referenced studies seek and select a cost-optimal package, the first objective of this study is to define the input parameters of a holistic LCC calculation and quantify their individual and combined influence on the output. This is accomplished using local (OAT) and global (MC) methods for the variation of the inputs as described in [14], and further discussed in Sections 2.2 and 2.3, respectively. The variation is applied to a pre-selected baseline model that represents a renovation package for a multi-family apartment building complex in Denmark.

The selected baseline model was found to be cost-effective by using a method proposed in the previous work of the authors of this paper [28]. Using the method proposed in [28], renovation packages are compiled based on a cost-effectiveness parameter of individual energy-saving and energy-producing actions. The second objective of this study is to test the robustness of the selected cost-effective baseline by comparing the obtained output variation in global cost to the results of other packages studied in [28].

This paper presents local and global sensitivity analyses applied to the selected baseline model. The local sensitivity (OAT) analysis, presented in Section 2.2, is performed for the model's boundary conditions and building the model's inputs. In addition, to investigate the influence of the energy supply type on the results, the energy supply system for space heating and domestic hot water (DHW) in the baseline is also variated between three alternatives: district heating (DH), a ground source heat pump (HP), and natural gas. For each energy supply system, an OAT analysis is applied to find the five input parameters with the most substantial influence on the output. To investigate the possible interactions of the parameters and their correlation, these five input parameters are further variated simultaneously using the MC approach with quasi-random sampling, described in Section 2.3.

2. Method

The work presented in this paper aims to determine the impact of boundary conditions and model input on the output of an LCC calculation, concerning the renovation of a multi-family building located in Denmark. To do so, first, the origin and key details of the applied baseline are presented. Thereafter, Section 2.1 describes the applied LCC calculation method, whereas Sections 2.1.1 and 2.1.2 depict boundary conditions and building-related model inputs, respectively. The local sensitivity of each model input is determined by performing OAT variation method as in [16,18] and further described in Section 2.2. The five most sensitive parameters to the output, found via the OAT method, are further applied in the global sensitivity analysis. Global sensitivity consists of simultaneous variation of inputs [15–17,24], where the method applied in this paper includes Monte Carlo (MC) method with Sobol sampling, described in Section 2.3. Finally, the sensitivity of the different parameters is analyzed using regression methods, described in Section 2.4. Figure 1 illustrates the approach used to define the input parameters and quantify their sensitivity.

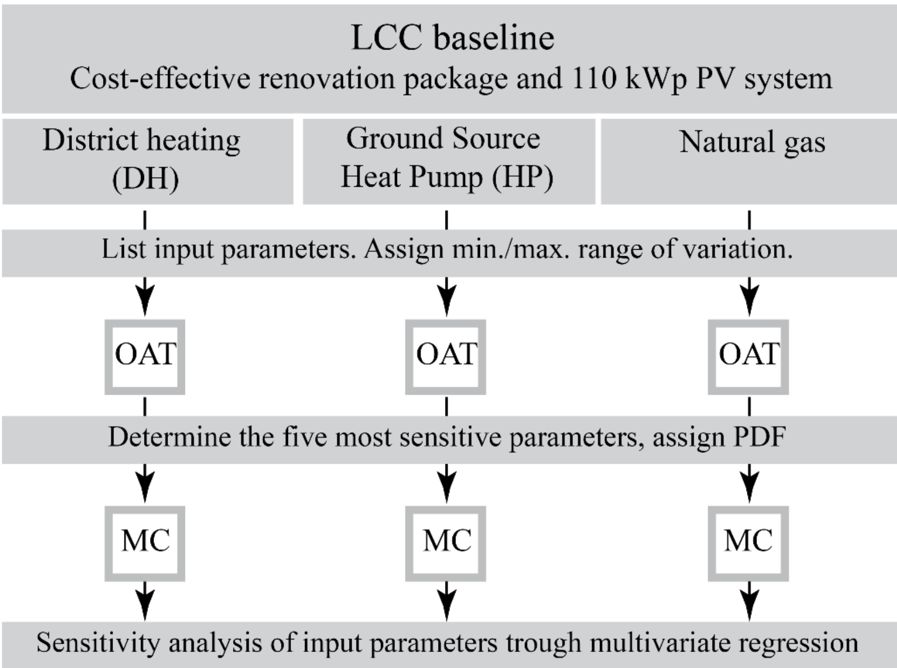


Figure 1. Diagram of sensitivity study applied in this paper.

For this study, the case building investigated in [28,29] is used as a starting point for the analysis. The building has been operational since 1949 and houses 66 apartments with a total heated floor area of 5250 m^2. The existing source of heating and DHW is a District Heating (DH) substation. The primary energy demand of the building in its existing condition, determined by the Danish compliance tool BE18, accounts for 130 kWh/m^2 per year [28]. The selected renovation package, represented in the baseline model, achieved approximately 40% energy savings and consists of the installation of new windows (energy class B); replacement of the circulation pump for DHW; re-insulation of the external wall, attic slab, and pipe networks for distribution of heating and DHW; and 110 kWp roof-mounted Photovoltaic (PV) system [18].

As indicated previously, the baseline is suited to three different energy supply systems for space heating and DHW. The scenario with a new DH substation considers costs related to replacing the existing sub-station. In the other two scenarios, the existing DH substation is replaced with a heat pump (HP) and natural gas boiler. Switching from DH to natural gas or HP as a supply source accounts for removing the DH sub-station and incorporating gas boiler or ground-source HP, respectively. Thereby, each of the three models have common (renovation package-related) and individual (system-related) input parameters.

2.1. Life Cycle Cost Calculation Method

The procedure and calculation methodology for LCC follow the standard DS/EN 15459-1:2017 [9]. Overall, a calculation model consists of boundary conditions and building-related model inputs. Boundary conditions include the calculation period and macro-economic factors for the calculation, i.e., interest rate and price development. The model input can be split into different categories, depending on the cost type, e.g., energy supply, acquisition, management, cleaning, component, recurring and non-recurring costs. Income from rent, incentives, loans, or grants can also be integrated into an LCC calculation. Commonly evaluated outputs of LCC are global cost (*GC*) or net present value (NPV), depending on the objective of the calculation. Global costs are calculated using Equation (1), shown with the same notation as given in standard [9]. The main difference between *GC* and NPV is that *GC* includes emission costs by definition. Those, however, are often excluded, and therefore the NPV can be considered the same as *GC*. Carbon costs are excluded from the analysis of this study as the monetary value of carbon costs and their future development is still quite uncertain, which applies to the consistency and comparability as well [28].

$$GC = CO_{INIT} + \sum_j \left[\sum_{i=1}^{TC} \left(CO_{a(i)}(j) * \left(1 + RAT_{xx(i)}(j)\right) + CO_{CO_2(i)}(j) \right) * D_{f(i)} + CO_{fin(TSL)}(j) - VAL_{ft_{TC}} t(j) \right] \quad (1)$$

where:

- CO_{INIT}—initial cost;
- CO_a—annual cost;
- CO_{CO_2}—emission cost;
- $CO_{fin(TSL)}$—disposal cost;
- VAL_{ft}—residual value;
- D_f—discount factor;
- t_{TC}—calculation period;
- $RAT_{xx(i)}$ price evolution of parameter *i*.

To a great extent, the model inputs are dependent on the aim, scope, and purpose of the performed study. Since this study adopts a baseline from previous research of the authors of [18], the model inputs are pre-determined. The selected baseline model accounts exclusively for costs related to the energy renovation of the selected package and building operation. That includes the cost for the purchase of building components and associated energy supply systems, and their installation, maintenance, replacement, and operation (supplied energy). LCC calculations are performed using the free software LCCByg (version 3.2.14) [30]. The considered model output, NPV, is used to determine the sensitivity and correlation of the variated input parameters.

2.1.1. Model Boundary Conditions

Boundary conditions in LCC refer to the calculation period and financial input parameters determined on a national level. In Denmark, the Ministry of Finance enforces discount rates (DR) and price developments (PD) for discounting future to present values. Guidance describing different DR types and their respective applications was published on 12 November 2018 and updated on 7 July 2021 [31]. The main difference in the letter was its lowered DR with 0.5% point in the updated 2021 guidance compared to 2018 values [32].

The guideline enforces a stepwise decrease in the real DR for public clients, as illustrated in Figure 2 (left). The applied LCCByg software provides two additional sets of assumptions: fixed real DR and fixed nominal DR. The respective values for each DR type are illustrated in Figure 2 (left), whereas a general description of the applicable building projects is outlined below.

- Decreasing real DR—This DR type is applied to public buildings where a 1% decrease is applied after years 36 and 75. This DR type applies fixed prices without inflation [32].
- Fixed real DR—Applied to projects concerning social housing organizations. As the name suggests, the DR and possible PD are fixed and exclude inflation.
- Fixed Nominal DR—Prices and DR are stated in current prices, including inflation. This DR type is applied to projects requiring DGNB certification.

Optionally, a specific PD can be applied for different cost types considered in the calculation. Those can be observed in Figure 2 (right). If applied, the individual PD is used instead of the general PD (inflation). The baseline models in [18] apply PD to energy costs for building operation, underlined in Figure 2 (right), to the respective energy supply system. For example, PD for gas and electricity in a scenario with natural gas boiler and only PD for electricity in the HP scenario.

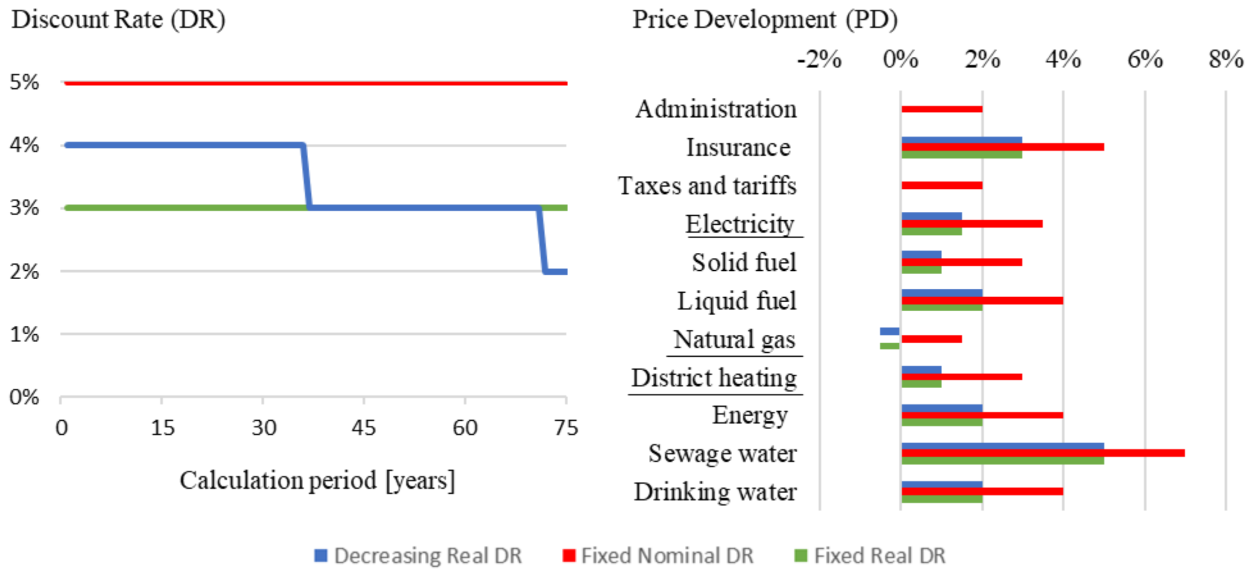


Figure 2. Discount rate types (**left**) and price development for different cost types (**right**). Data source [31].

To investigate the impact of the three DR types on the resulting NPV, they are applied to the baseline model, using the OAT approach. Additionally, the impact of applying the optional PD for DH and electricity is investigated by computing the DH baseline model with and without PD for each of the DR types.

2.1.2. Model Inputs

A list of all calculation inputs included in the three variations of the baseline model is presented in Table 1. The table classifies the input parameters into five categories and depicts the baseline value and respective source. Model-specific parameters describing the variated energy systems are marked with a "*" before the parameter name. These parameters are only applied in the appropriate models. The first three cost categories in Table 1 (operation, implementation, and maintenance) are unit cost inputs. The last two are the lifespan of the elements and the amount (quantity) for each parameter.

Table 1. List of input parameters.

			Baseline		OAT	
Category	**Parameter**	**Unit**	**Value**	**Source**	**Range**	**Source**
Operation (Energy supply)	* District heating	EUR/MWh	69.29	DEA [33]	18–128	Database min/max
	* Gas	EUR/m^3	0.796		0.635–0.913	
	* Electricity	EUR/MWh	230.1		210–330	
	* Electricity-HP	EUR/MWh	93.54		-	
Implementation	* DH sub-station	EUR/system	15,600	TDC [34]	12–20 K	TDC [25]
	* Gas boiler	EUR/unit	24,600		20–30 K	
	* Heat Pump	EUR/unit	249,000		235–265 K	
	Roof-mounted PV	EUR/system	80,300	TDC [35]	49.5–134.2 K	Assumed ±20%
	Ex. wall insulation	EUR/m^2	20.7	MOLIO [36]	17–25	Assumed ±20%
	Ex. wall cladding	EUR/m^2	17		13–20	
	New windows	EUR/m^2	73		69–88	
	Attic insulation	EUR/m^2	130		104–156	
	Pipe network ins.	EUR/m	11.8		9–14	
	Circulation pump	EUR/unit	1098		879–1318	
Maintenance	* DH sub-station	EUR/year	136	TDC [34]	108–189	TDC [25]
	* Gas boiler	EUR/year	651		531–814	
	* Heat Pump	EUR/year	1650		1070–2850	
	Roof-mounted PV	EUR/year	1144	TDC [35]	781–1342	TDC [26]
	Ex. wall insulation	EUR/year	551	LCCByg*	440–660	Assumed ±20%
	Ex. wall cladding	EUR/year	894		715–1072	
	Windows	EUR/year	1147		918–1376	
	Attic insulation	EUR/year	228		1814–2722	
	Pipe network ins.	EUR/year	373		298–447	
	Circulation pump	EUR/year	11		9–13	
Lifespan	* DH sub-station	year	25	TDC [34]	20–30	TDC [25]
	* Gas boiler	year	25		25–40	
	* Heat Pump	year	20		15–25	
	Roof-mounted PV	year	30	TDC [35]	25–40	TDC [26]
	Ex. wall insulation	year	50	sbi [37]	40–60	Assumed ±20%
	Ex. wall cladding	year	120		95–145	
	Windows	year	50		40–60	
	Attic insulation	year	50		35–65	
	Pipe network ins.	year	80		65–95	
	Circulation pump	year	25		20–30	
Amount	* District heating	MWh	483.37	calculated BE18	387–580	Assumed ±20%
	* Gas	m^3	CC			
	* Electricity—DH and gas	MWh	51,072		41.6–62.4 K	
	* Electricity—HP	MWh	216.8			
	Ex. wall insulation	m^2	2660	Measured	2128–3192	Assumed ±20%
	Ex. wall cladding	m^2	2660		2128–3192	
	Windows	m^2	1570		1256–1885	
	Attic insulation	m^2	1750		1400–2100	
	Pipe network ins.	m^2	3160		2528–3792	

LCCByg*—standard values in the software, based on sbi [37]. A "*" denotes the parameters applied exclusively in the respective models, representing alternative energy supply systems.

Costs for energy renovation measures were obtained from the MOLIO price database for renovation works [36]. Costs related to energy-producing systems stem from Technology Data Catalogues (TDC) for individual heating installations [34] and energy-producing technologies [35]. The lifespan of envelope elements is taken from guidelines [37] and TDC [34,35] for energy supply systems. The energy demand for the operation of the building includes the energy necessary for space heating, DHW, and electricity (both for building operation and private use). Building operation-related electricity is determined by the compliance tool BE18. Private electricity demand is determined through metered data at the building, collected during an energy audit described in [29]. The energy demand is calculated by the Danish compliance tool BE18 and already accounts for energy savings, which were achieved by the implementation of the renovation package and the energy produced by the roof-mounted PV [28]. The improved building element (m^2; m; piece) is determined through documentation and building audit, presented in [29].

The lower and upper bounds for the uncertainty range of the different parameters are shown in Table 1. Unit cost for represented energy sources is determined from available data in the price database published by the Danish Energy Agency (DEA) [33] in 2018. The granularity of the different energy supply sources differs for DH, gas, and electricity. The baseline model's district heating unit cost is determined by averaging the available data for 392 different locations across Denmark (2018 database). Electricity unit cost data are available as annual values, categorized with respect to usage type (household or industry) and consumption range. The baseline unit cost for electricity is selected as the average annual household electricity price excluding VAT, taxes, and levities, for the period from 2007–2018 as well as lowest consumption range. Gas unit cost originates from the same period, though using monthly instead of annual data points. The unit cost of the different energy sources and the determination of their applied variation are discussed further in the following sections of this paper.

2.2. Local Sensitivity Analysis—OAT

Local sensitivity analysis in this paper refers to a one-at-a-time (OAT) variation of input parameters. Having the baseline as a starting point, each input value is variated consecutively, while the remaining parameters are kept constant. The OAT analysis is performed twofold, distinguishing between variations of boundary conditions (see Section 2.1.1) and building-specific model inputs (see Section 2.1.2).

The baseline represents a multi-family building owned by a social housing association. Ergo, respecting the DS/EN 15459-1:2017 [9] guidelines for such building type means applying a decreasing real DR for a 50-year calculation period. As previously pointed out, PD for energy costs has been considered in the respective models. However, to assess their direct effect on the output, PD for electricity and DH are variated in addition to DR type and calculation period.

First, the three different DR types described in Section 2.1.1 are applied in turn to the baseline. For each of the DR types, the calculation is performed for a range of calculation periods from 10 to 60 years with a 10-year step interval. In addition, price development for electricity and district heating are applied individually and in combination for each DR type and calculation period. OAT analysis for DR types and specific PD were applied only to the baseline model that utilizes district heating as the main supply for heating and DHW. This was performed to quantify the difference between applied DR, PD, and for variation of calculation period.

Given that the building is owned by a social-housing association and provided that for this type of client (public), one must follow the Ministry of Finance [32], the DR can be considered a deterministic model input. This is because the discount rate is determined by the standard, meaning that a designer is obligated to apply a specific value. Boundary conditions are thus variated by OAT only, with the purpose of quantifying possible output variation for the different DR types, price developments, and calculation periods.

The second step in the OAT approach consists of variating model input parameters related to the specific building renovation. In this case, this entails the input parameters that make up the baseline. Two variations for each parameter are performed—one with the lower and one with the upper value of uncertainty, defined in Table 1.

Evidently, the ranges for different parameters in Table 1 are obtained from different sources. Costs related to energy supply and renewable systems are obtained by the two Technology Data Catalogues (TDC) published by the Danish Energy Agency (DEA) [34,35]. Costs related to renovation works and energy efficiency improvements originate from the MOLIO database [36], whereas the applied ranges are assumed due to a lack of a better source. Lastly, the cost for the operation of the building stems from the DEA's historical energy price database from 2018 [33]. The unit cost for energy types used in the baseline and variation ranges applied in the OAT calculations are determined as follows:

- District heating (DH)—the unit price for district heating is available for 392 DH plants across Denmark. There is great variation in the cost of delivered heat across Denmark. Therefore, cost data in [38] are given as annual values for 2018—found in the 392 different DH plants and not as historical values—for electricity and gas. The average price for 2018 from the different stations is 525 DKK/MWh and varies significantly from one DH plant to the next (±135 DKK/kWh). The range for OAT calculations is determined by the minimum and maximum value, accessible in the database.
- Electricity—the unit cost of electricity is a quite complex and uncertain parameter. The final unit cost depends on the "raw" energy price and several other factors influencing the price. Some of the main factors are governmental fees and taxes, provider subscription expenses, network maintenance, and fees. Moreover, some of those fees are fixed while others are added concerning the building heating system and demand. For example, a general charge of 88.4 øre/kWh is added to the electricity price. If the building is heated by electricity, an additional 25.9 øre/kWh is owed by each client (building owner) [38]. Moreover, a variable "PSO (Public service obligation)" is added when forming the final electricity price. As all of those price elements are highly variable and continuously evolving, they are thereby excluded from the calculations along with VAT, taxes, and fees. In addition to all taxes and fees, electricity price is also dependent on the annual amount of purchased electricity by the "client" of the energy providers, e.g., apartment tenants or building owners. Clients of a supply company are classified into categories (usage intervals) from small (single-family homes) to large (industrial clients). Naturally, the unit cost for large clients is lower than that for small clients. As the baseline considers a multi-family building, the baseline value was selected considering medium-size client (usage interval from 2.5 < 5 MWh) and determined as the average of available annual cost data for 2009–2018 [33]. It should be pointed out that the analysis presented in [28] and those presented in this paper account for the purchase of electricity for the whole building globally (e.g., building operation and private use in apartments are analyzed as inputs). In reality, the building owner and each tenant would be individual clients of the electricity provider. Thus, tenants would be categorized/charged according to costs with respect to low usage intervals, while the building owner would likely be categorized as a client in the higher usage intervals with lower unit costs. The range applied in OAT analysis represents the minimum and maximum annual values for electricity costs of different usage intervals to investigate the effect of this simplification.
- Gas—unit costs for gas are also differentiated by client type (household or industry) and by the amount of purchased energy. A breakdown of household gas prices is provided monthly for the period from 2009–2018. Each aspect contributing to the total gas price is represented individually. Given that the gas price has been rather stable [33] for the period from 2009–2018, the baseline value was determined by average cost, while the OAT range was determined as the minimum and maximum values for the whole period and excluding VAT. Gas prices are also available as annual values for different usage intervals (client sizes). In a scenario where gas is the source for centralized heating and DHW supply, the energy demand of the building would be a determining factor for the unit cost of gas. However, just as for electricity, governmental taxes and local subscription tariffs are also major determining factors for the total cost. Those are included in the OAT variation, as the baseline adapts average, minimum, and maximum values from 2007–2018, excluding VAT but including government taxes and levies. Furthermore, baseline values were selected based on the smallest available usage interval (<20 GJ gas).

Ranges for implementation, maintenance, and lifetime of the energy systems are referenced in Table 1 TDC [34,35]. The variation ranges for energy efficiency improvements are determined as ±20% variation from the baseline due to the lack of a better source. The same ±20% are applied to the quantity of the different material inputs. These variations, for instance, could result from false quantity estimations related to different renovated building parts or insufficient documentation, leading to uncertain assumptions.

Once all variations are computed with their respective minimum and maximum values, the sensitivity index of each parameter is determined by Equation (2). The parameters are sorted in ascending order with respect to the calculated sensitivity index. This procedure lists the most influential inputs to the output parameters first and allows for the selection of the desired top five most influential inputs.

$$SI = \frac{\Delta y_i}{\sum |\Delta y_i|} \tag{2}$$

where Δy_i is the difference between the output values obtained from the minimum and maximum variated input value of parameter i.

2.3. Global Sensitivity—Monte Carlo (MC) Method

Contrary to the OAT approach, the MC method allows for the quantification of the combined (global) effect of the variated parameters. This is achieved by continuously reproducing calculations of the baseline model, where selected input parameters are variated simultaneously based on random or quasi-random sampling techniques. The sampling applied in this paper is realized by Sobol sequencing for the selection of the quasi-random samples. Quasi-random sampling allows for better coverage of the solution space than random sampling, as clusters of closely distributed input values are avoided [16].

The sequence for a successive step in the analysis consists of generating the quasi-random value in the range of 0–1, which is then used to select the values for variated inputs via cumulative Probability Density Functions (PDF) for each parameter. The procedure is performed for the total number of chosen samples, which is 5000 for each supply system. Once all sample inputs have been determined and saved into an input matrix, AutoIT script is applied to compute each set of inputs in LCCByg and export the results. The procedure is then repeated for all samples.

As previously explained in Section 2.2, the parameters variated in the global analysis are selected with respect to their sensitivity indices. Once the parameters are identified, the ranges and data availability used in the OAT approach are examined in detail. This is completed to assign appropriate PDFs for the parameters with respect to the parameter type, available data, and identifiable forecasting trends. Performing such a study for all input parameters would be tedious, lengthy, and to some extent redundant work. Therefore, a detailed investigation of applicable data is performed solely for the parameters, selected from the OAT approach. The selected parameters used in the global sensitivity method and their distribution types and ranges are presented in Section 3.2.1.

2.4. Sensitivity Analysis

Sensitivity analysis is applied to assess the relationship between inputs and outputs and to compare models with alternative energy supply systems for space heating and DHW. Determining how each input contributes to the output is performed by carrying-out multivariate linear regression analysis employing estimates known as Standardized (Rank) Regression Coefficients (S(R)RC). It is based on a standardized input matrix and output vector, demonstrated in Equation (3) for each of the inputs ($x_{j,i}$) and the output ($y_{j,i}$).

$$std\_x_{j,i} = \frac{x_{j,i} - \mu_x}{\sigma_x},\ std\_y_{j,i} = \frac{y_{j,i} - \mu_y}{\sigma_y} \tag{3}$$

The standardized coefficients are then used for the regression model, which applies the least-squares method to calculate a line fitting Equation (4) for the five inputs (x_1–x_5) and output data (y_1).

$$std\_y = b_1 std\_x_1 + b_2 std\_x_2 + \ldots + b_n std\_x_n \ldots + \varepsilon \quad (4)$$

where b_i denotes the regression coefficients responding to each x_i parameter and ε is a constant.

The obtained regression coefficients (*bi*) are used to determine the importance of the respective input, as its value quantifies its sensitivity. The larger the coefficient, the more sensitive it is. The sensitivity index (*SI*) is estimated as the relative share of each regression coefficient to the absolute sum of all coefficients, as illustrated by Equation (5).

$$SI_{x(i)} = \frac{b_i}{\sum |b_i|} \quad (5)$$

Given that the applied regression model is linear, the standard coefficient of determination (R^2) is assessed to verify or disprove the linearity of the baseline model. The R^2 value ranges from zero to one and represents the difference between estimated and actual y-values. R^2 value close to one indicates a good correlation of the studied sample, thereby a linear LCC calculation model. On the other hand, if the R^2 value is closer to zero, the linear regression is not suitable for predicting the output.

3. Results

3.1. Local Sensitivity—One-at-a-Time (OAT) Approach

This section presents the results from the OAT approach, which is performed in two stages: one for the boundary conditions and one for the model-specific input. First, Section 3.1.1 presents the results from the variation of the discount rate (DR) types and calculation periods, defined in Section 2.1.1. Second, the building-related model inputs are variated with their minimum and maximum values and presented in Section 3.1.2. The section also presents the sensitivity of each parameter and which five are chosen for variation in the global MC method.

3.1.1. Boundary Conditions

The results concerning the DR type and individual price developments (PD) are presented in Figure 3. The sensitivity index depicted on the y-axis of the figure is calculated using Equation (2), where Δy for each case is calculated based on the financial conditions of the baseline, i.e., a decreasing real DR, a 50-year calculation period, and by disregarding specific price developments. Given this consideration, the positive sign index represents scenarios with a greater global cost than the baseline. As evident from Figure 3, the variation from the baseline due to PD is relatively small (<0.1). When comparing the two different PD to the baseline model (decreasing DR), it can be noticed that, when applied individually, the PD for DH has a higher impact than the PD of electricity for all DR types. The combined effect on the result when the PD for both energy sources are applied is slightly lower for real DR types and additive for fixed nominal DR.

Figure 4 shows the sensitivity index for the DR rates calculated for different periods disregarding the PD. The calculation period affects the results nearly linearly, which was recognized due to a proportional change in the sensitivity index with a change in the calculation period. The difference between the successive calculation steps is nearly equal, but an increase in the index is noticed for the shortest calculation periods. Overall, it can be stated that the calculation period is the boundary condition that will have the greatest influence on the final result, compared to the DR and the application of PD. A 10-year difference in the calculation period results in greater change in the output than applying different DR or PD.

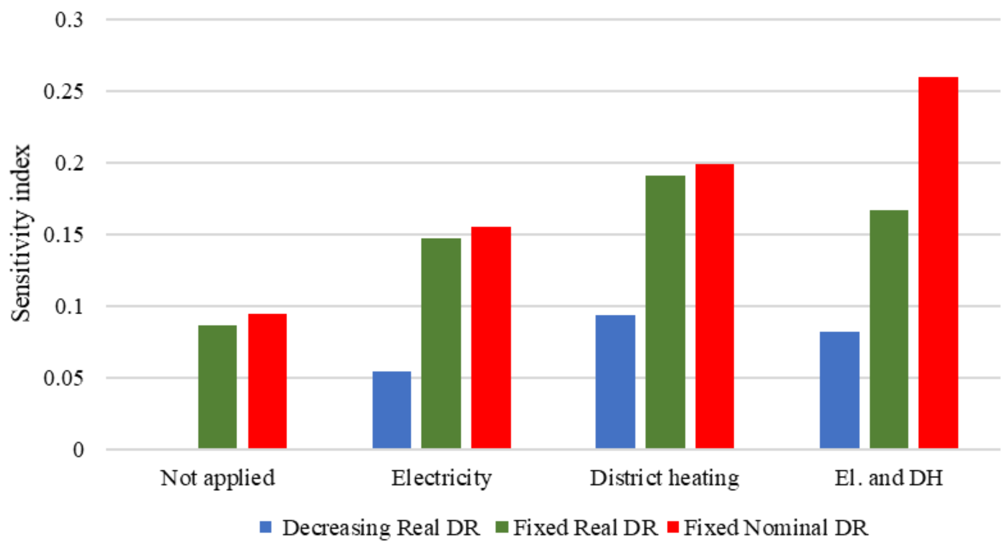


Figure 3. Sensitivity index for different discount rate (DR) types and price developments (PD) compared to the baseline (decreasing DR and no applied PD), considering 50-year calculation period.

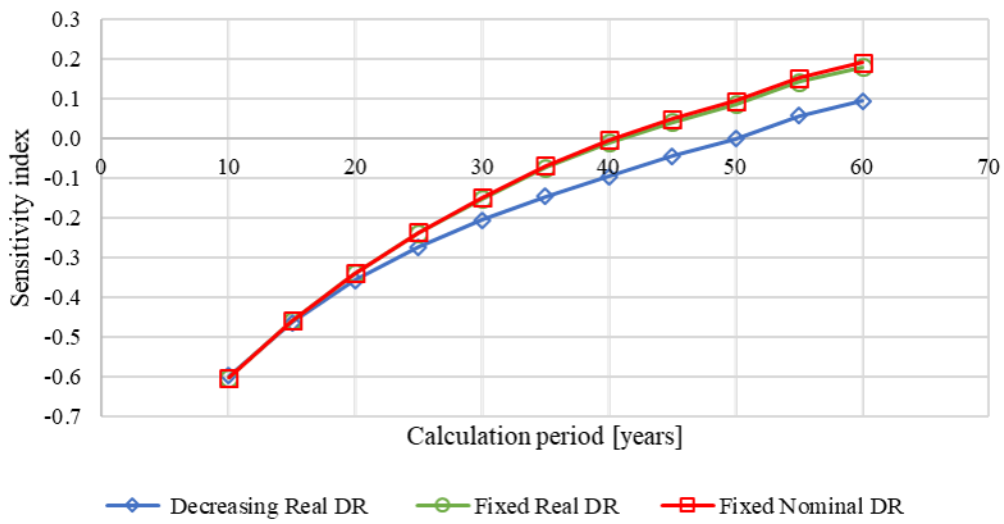


Figure 4. Sensitivity index for three discount rates (DR) as a function of calculation period.

3.1.2. Model Inputs

The second investigation employing OAT methodology was applied to building-related model inputs, defined in Table 1. As described in Section 2.2, the OAT calculations of the model inputs are used to identify the most impactful parameters for the output—in this case, the NPV. Figure 5 shows the sensitivity index of each parameter and each investigated energy supply system. The sensitivity indexes depicted in Figure 5 are calculated following Equation (2) for the respective ranges stated in Table 1.

For the three investigated systems, the parameters related to the fuel cost and amount rank highest. An exception is present in the Heat Pump (HP) scenario, where the lifetime of the HP outranks the electricity amount with the second-highest sensitivity index. A plausible explanation for this is the high investment (and thereby replacement) cost of a HP. Applying the upper and lower limit values for the HP's lifetime in the OAT variation results in one extra or less system replacement for the calculation period. The remaining parameters that follow the fuel cost seem to be ranked (positioned), if not in the same order, then very close to the same order—all the way to the least sensitive inputs.

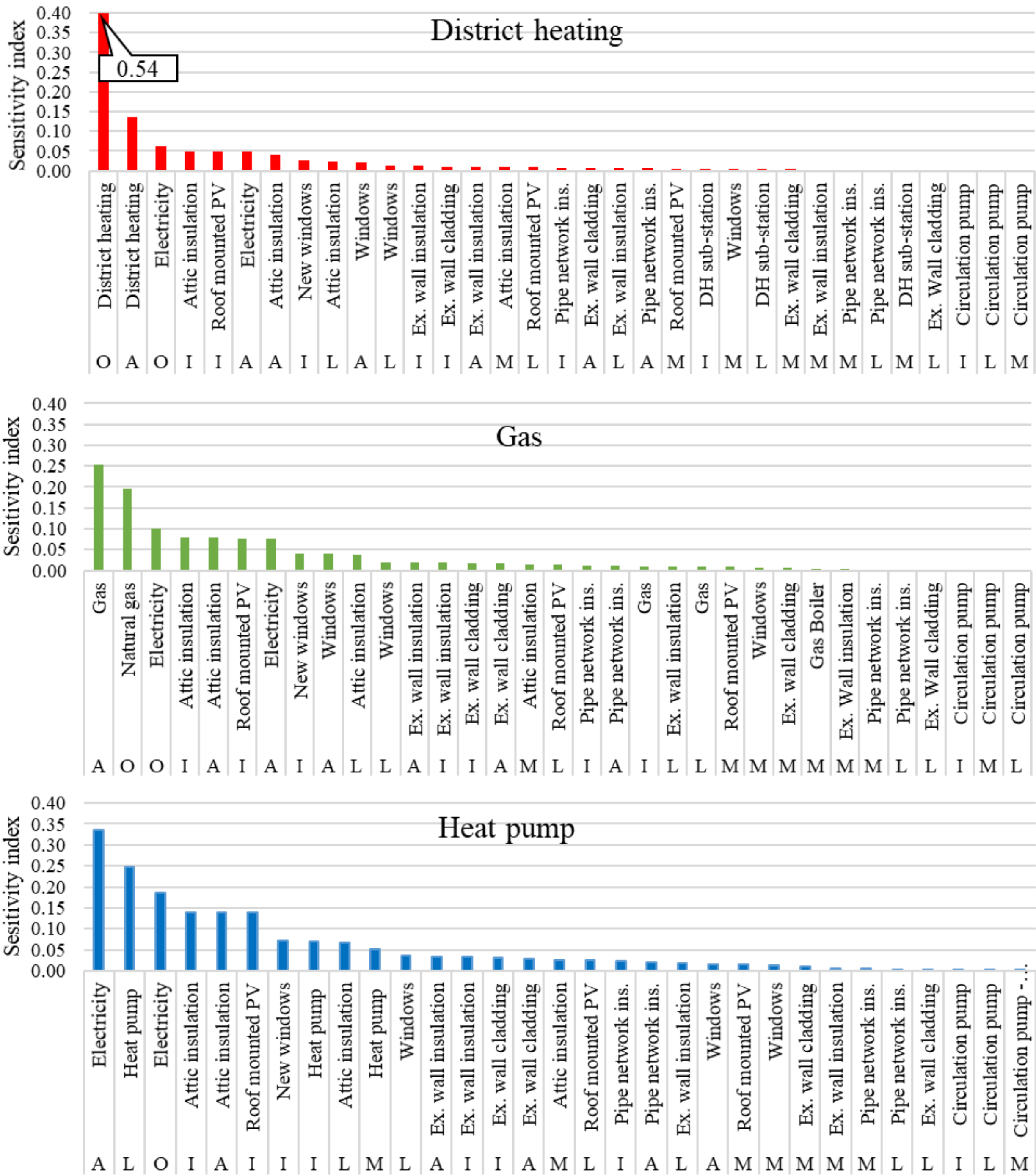


Figure 5. Results from variating input parameters using OAT approach. Capital letters represent the input category: O—operation, I—implementation, M—maintenance cost, L—lifetime (years), and A—amount (kWh, m^2, m^3, etc.).

Despite their front-ranking position, the parameters describing the amount of electricity, gas, and district heating energy were excluded from variation in the global analysis. This decision was made because the sensitivity of energy demand is a topic of its own that is highly dependent on the method for deriving the final value of the delivered energy. The results in Figure 5 show that the amount of energy has a significant influence, regardless of the applied system. Therefore, one should be sure of the value's origin (or used method) when striving for a high-accuracy LCC.

In contrast, the unit cost of the different fuels is considered in the global sensitivity analysis. Energy unit costs are also a rather complex parameter. The main uncertainty in the development of the fuel cost lies in the stability of the global energy market as well as national and local factors (subscription fees, local rates, and building usage type). The energy unit cost can be quantified by historical and/or forecasted data. In this study, the price variation for electricity and gas is determined based on historical and forecasted data, stemming from supply plants operating with various sources and different principles. As evident from the DEA database [33], those are also characterized by different costs. While the unit cost varies on a national level, the value for a specific building depends on the location. Therefore, the DH unit price is considered deterministic since the owner would have to pay the cost of DH for the region where the building is located. Regarding the results shown in Figure 5, the DH unit cost presents the single largest sensitivity index. Due to its deterministic essence, the DH unit cost is not varied with the MC method; however, it is still accounted for in the analysis. This is performed by accounting for the large national price variation by fixing the DH unit cost at a low, medium, and high value and variating the next five most impactful parameters. The low and high DH unit costs are chosen as 2σ from the mean value (low = 34, medium = 68, and high = 108 EUR/MWh). In essence, three variations incorporating the aforementioned DH prices are calculated for the DH scenario. This method is applied to quantify the relative importance and possible interactions of the next five parameters with the DH unit cost. Furthermore, it is also applied to identify if any changes occur in the relationship between inputs and output caused by the level of DH unit price. The parameters variated in the MC analysis for each system type are summarized in Table 2 and discussed in detail in the following section.

Table 2. First five most sensitive parameters for each system, excluding the energy required for building operation. Background color identifies identical input parameters for each energy supply system.

	Rank according to Sensitivity Index				
	1	**2**	**3**	**4**	**5**
District heating	unit cost electricity	unit cost attic insulation	unit cost roof PV	amount attic insulation	unit cost new windows
Heat pump	lifetime heat pump	unit cost electricity	unit cost attic insulation	amount attic insulation	unit cost roof PV
Gas	unit cost natural gas	unit cost electricity	unit cost attic insulation	amount attic insulation	unit cost roof PV

3.2. Global Sensitivity

3.2.1. Variated Parameters

Table 2 summarizes the top five ranking parameters (excluding the amount of energy) for each scenario comprising different energy supply systems. Four of the parameters are common for all scenarios: the unit cost of electricity, attic insulation, roof-mounted PV's, and the amount (m^2) of attic insulation considered in the calculation. Besides the shared parameters, a model-specific parameter is identified for each of the three cases: for DH, it is the unit cost of the new windows; for HP, it is the lifetime of the ground source HP system; and for gas, it is the unit cost of the fuel.

As discussed in the previous section, the electricity price is a rather complex parameter to predict. Two of its determining factors are the annual amount of supplied electricity to the client and the type of heating system (e.g., electrical or another source for space building heating). In that sense, the "profile" of the building owner may change when switching from a fuel-based to an electrical heating system. This is firstly due to the larger amount of purchased electricity (usage interval); secondly, it is due to additional fees if the building is heated by electrical energy [38].

The unit cost difference in the electricity price can be observed in Figure 6, which shows historical and forecasted data for two distinct usage intervals for electricity and gas. The figure collects data from the DEA price database [33] and another DEA publication on socio-economic calculations, including the cost of energy [39]. The latter provides forecast values for electricity and gas costs for the period from 2020–2040. The forecast is based on 2019 values, where the electricity cost was disclosed for a single usage interval, while for gas, a forecast for several different intervals was available. The solid bars in Figure 6 represent electricity prices for the second largest interval (<15 MWh), while the patterned addition depicts the unit cost for the smallest usage interval (used to determine unit costs in the baseline model).

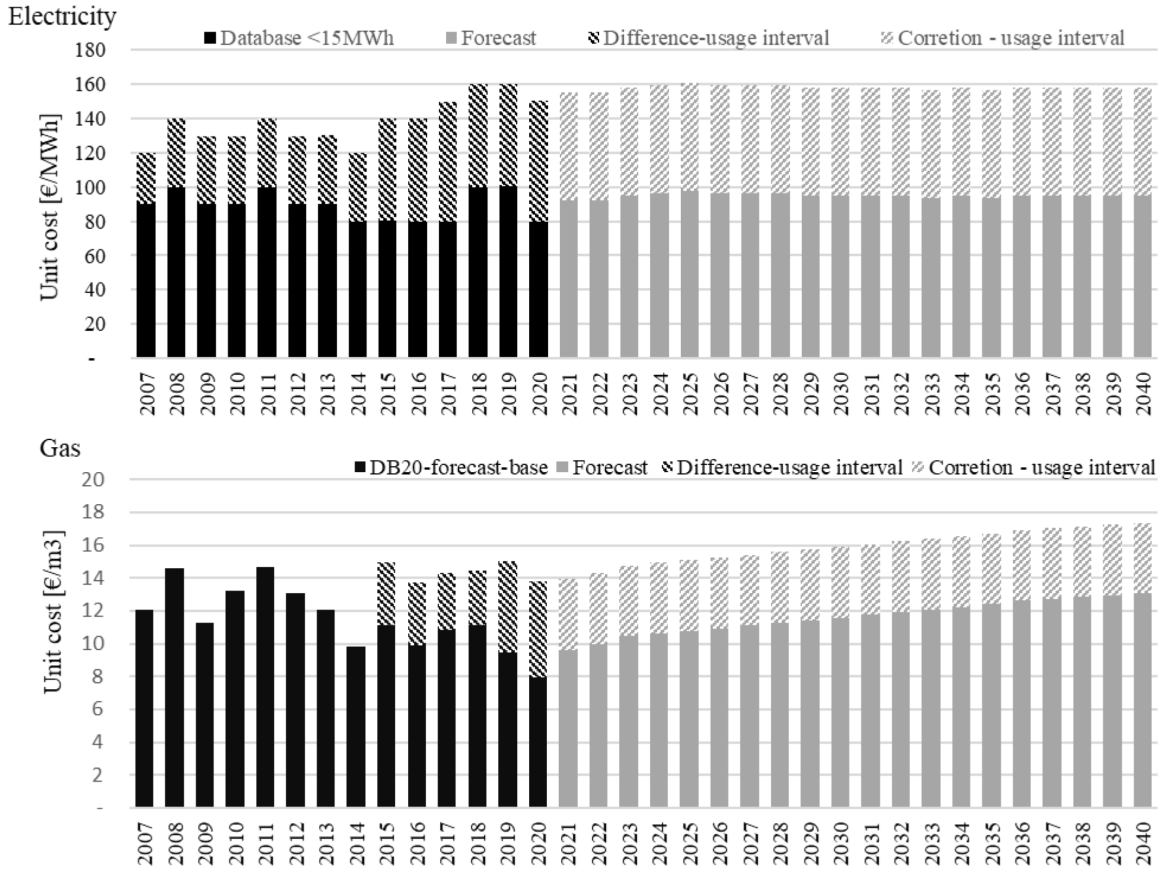


Figure 6. Historic (black) and forecasted (grey) values for electricity and gas. Diagonally filled pattern represents the unit cost difference for relevant usage intervals. Forecasted values are corrected for the applied usage interval in the simulations.

The electricity demand in the LCC model is represented by a single input value accounting for the total building demand (operation and private). The majority of the electricity demand in the DH and gas scenarios is attributed to private apartments, in contrast to the HP scenario where electricity for building operation accounts for approximately 80% of the total demand [28,29]. Thereby, for the DH and gas scenarios, the majority of electricity would be "paid" at the highest price (a low usage interval), whereas for the HP scenario, an increased electricity demand (101 MWh/y) classifies the building owner in the highest usage interval (>15 MWh). For 2018, the difference between the smallest and largest interval is 60 EUR/MWh el (approximately 60%). This difference is not taken into account for the HP scenarios in the analysis presented in [28]. From Figure 5 and Table 2, it is evident that the considered electricity price significantly impacts the output. The applied MC method accounts for price differences by using a PDF, derived from the low usage interval (<1 MWh; higher cost) for the models with DH and gas, and a PDF derived from the high usage interval (>15 MW; lower unit price) for the HP scenario. The PDFs for both usage intervals are shown in Figure 7 and are based on the last five annual historic data values (2015–2020) and all forecasted data points in Figure 6.

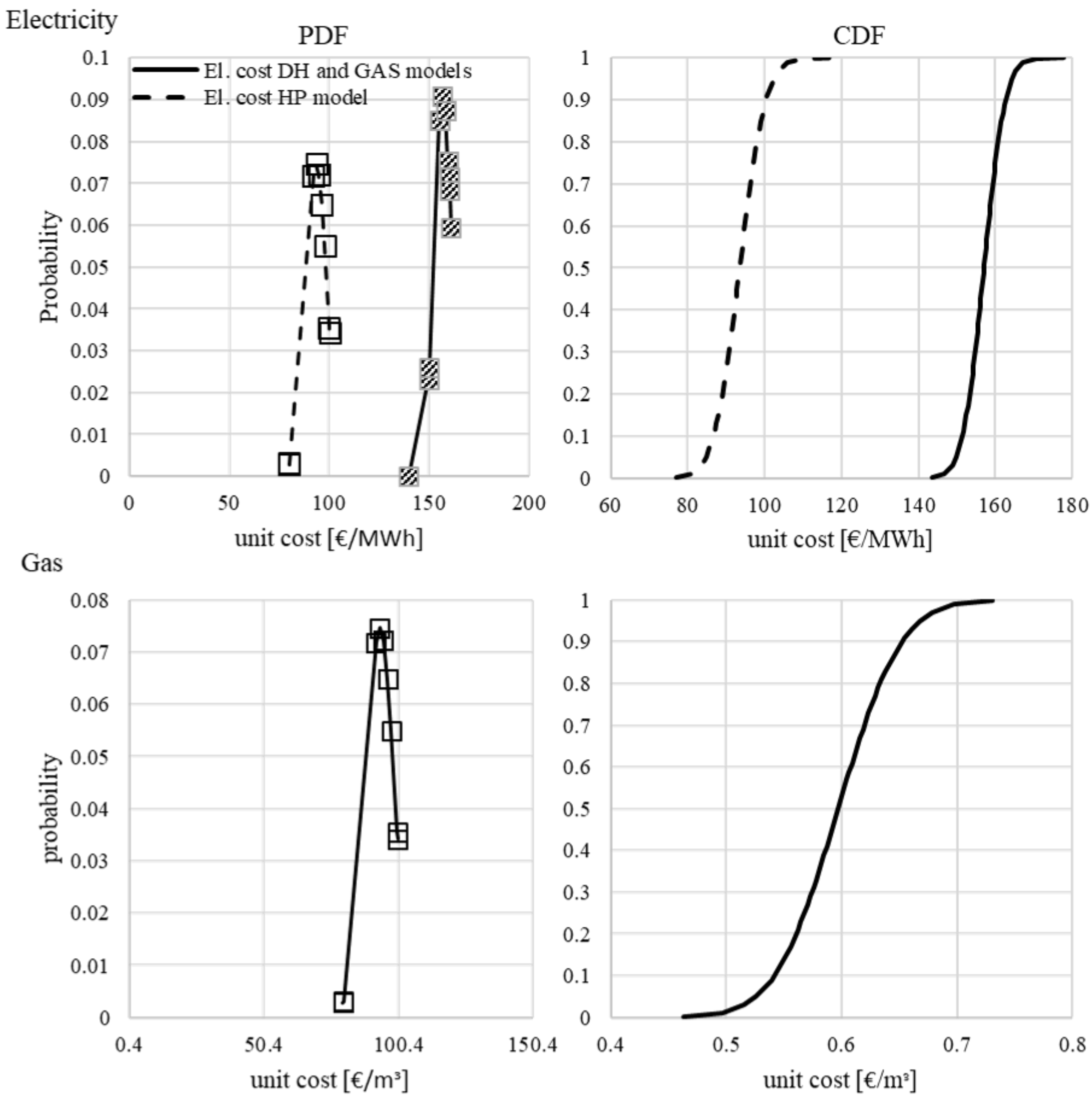


Figure 7. Probability density function (PDF—left) and cumulative distribution function (CDF—right) for electricity and gas, respectively.

As with electricity, the forecast for natural gas prices is provided in [33] for a higher usage interval than the one applicable to the investigated renovation package. The forecasted gas values are thus corrected (hatched pattern in Figure 6) in the same manner as those for electricity. Moreover, to increase the variation and anticipate the uncertain changes in the forecast, the data for determining the PDF and CDF of gas are based on the same interval span as for electricity: the corrected forecasted values and historical values for the period from 2015–2020.

The unit cost for the implementation of new windows is described by a normal distribution function. All the remaining parameters identified in Table 2 are variated utilizing uniform distributions with the ranges identified in Table 1. The applied variation range is based on energy class B windows, which differ in price due to the opening mechanism and frame material. The data used for the calculation of the standard deviation, mean value, and resulting PDF were acquired from the renovation cost analysis presented in [29]. Table 3 summarizes the variated parameters, their respective distribution types, sources, and limit values.

Table 3. Summary of variation parameters applied in Monte Carlo method.

Category	Parameter	Unit	Probability Density Function		Source
Operation	Electricity—DH and gas	EUR/MWh	Normal	μ = 157; σ = 4.39	DEA [37,39]
	Electricity—HP	EUR/MWh	Normal	μ = 93.5; σ = 5.35	DEA [37,39]
	gas	EUR/m^3	Normal	μ = 0.6; σ = 0.04	DEA [37,39]
Implementation	Attic insulations	EUR/m^2	Uniform	104–156	Assumed
	Roof-mounted PV	EUR/system	Uniform	49.5–134.2 K	TDC [35]
	New windows	EUR/m^2	Normal	μ = 147.1; σ = 50	Assumed
Lifespan	Heat pump	year	Uniform	15–25	TDC [34]
Amount	Attic insulation	m^2	Uniform	1400–2400	Assumed

3.2.2. Sensitivity Analysis

This section presents the results for all the models variated with the Monte Carlo (MC) method. To begin with, the results for the three models representing different fixed levels of DH unit costs are analyzed by histograms and calculated via cumulative distribution functions. Afterwards, the results concerning the parameter sensitivity and model linearity are presented.

The effect of the distinct, fixed unit costs of DH on the NPV output is shown in Figure 8. As can be observed, the spread and range of the variance of the results seem to be identical for the three cases. The magnitude of the output value differs due to the distinct unit cost of DH applied in each case (low = 34, medium = 68, and high = 108 EUR/MWh). The distribution, spread, and variance magnitude are identical. This was confirmed because the resulting standard deviation of each of the three distributions is equal (σ = 117,220 EUR). The mean value of the results for the low, medium, and the high price of the DH unit cost is −1.54, −1.93, and −2.31 million euros, respectively. This suggests that the DH unit cost also influences the result linearly. This can be stated due to (1) the equal variance of the three distributions and (2) the identical regression coefficients and R^2 values obtained from the regression analysis, presented in Appendix A.

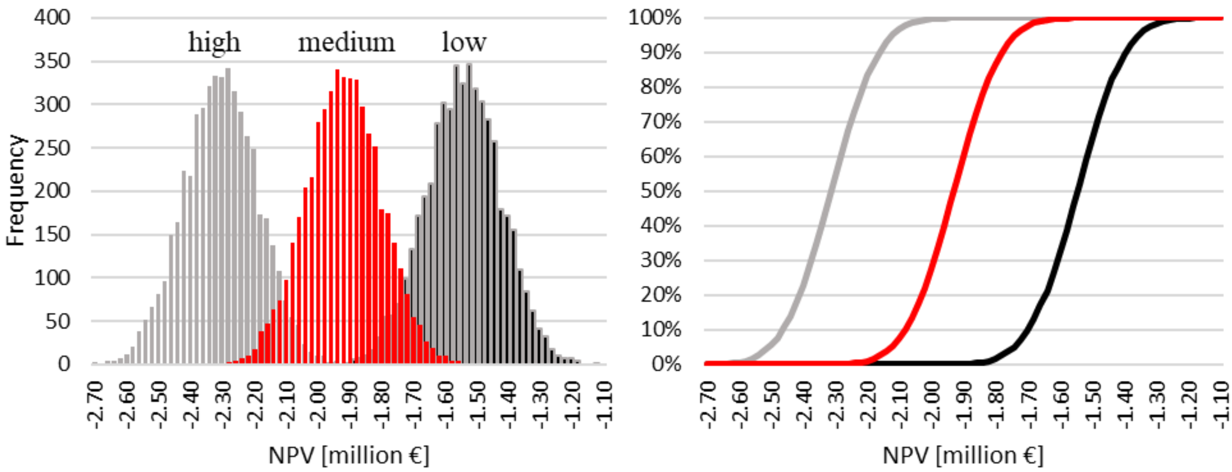
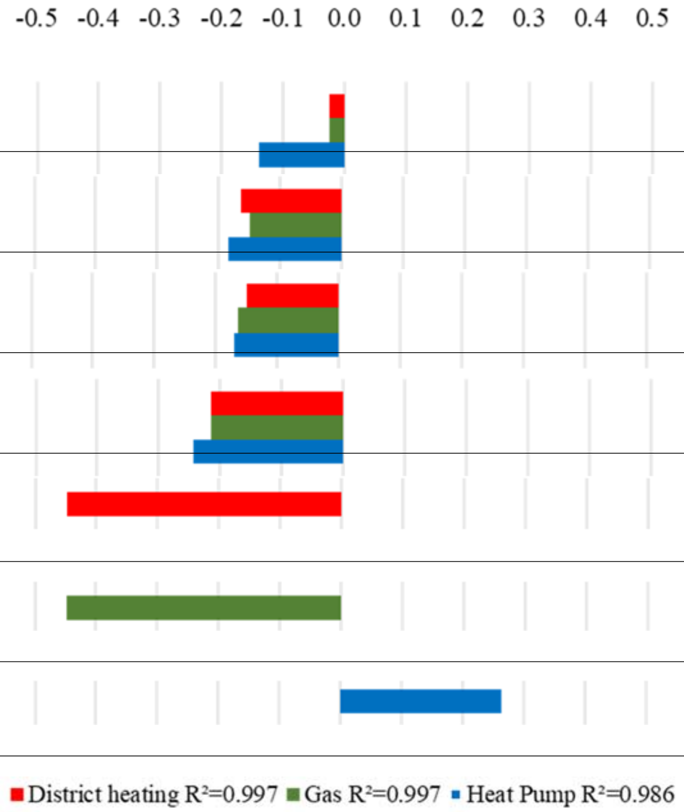


Figure 8. Probabilistic NPV for LCC calculation models incorporating three distinct unit costs for district heating.

Table 4 provides a summary of the multivariate regression results for each model. The first four parameters (the unit cost of electricity, attic insulation and PV, and the amount of attic insulation) are common for all models. All four are variated in every model. In contrast, parameters 5, 6, and 7 are specific for the DH, gas, and HP models. The complete regression results for each model variation is available in Appendix A.

Table 4. Summary of linear regression results for the three investigated space- and DHW heating systems.

Nr.	**Variable**	**Sensitivity**	**Standardised Regression Coefficient (SRC)**		
			DH	GAS	HP
1	Electricity unit cost		−0.029	−0.067	−0.303
2	Attic insulation unit cost		−0.299	−0.447	−0.400
3	PV unit cost		−0.237	−0.408	−0.366
4	Attic insulation amount		−0.393	−0.588	−0.526
5	**Model DH:** New windows unit cost		−0.823		
6	**Model: Gas** Gas unit cost			−1.229	
7	**Model Gas:** Lifetime of HP				0.57



All sensitivity indexes in Table 4, except the lifetime of the HP, are negative. This means that an increase in a variated value would result in a decrease in the output. Since the calculations consider only expenses (disregard positive cash flow/income), the NPV output is negative; therefore, decreasing the output asserts a more costly solution. The results of the DH and gas models suggest a close to equal importance for the four common parameters. The unit cost of electricity is the parameter with the most negligible influence on the output. For gas and DH, it is noticeably less impactful than the remaining variated inputs. The unit cost for attic insulation and the implementation of a PV system is the next most influential parameter, where minor differences can be noted for gas and DH. In the case of DH, the unit cost for the implementation of a PV system is more influential than the unit cost of attic insulation and vice versa for gas. The model-specific parameters in the DH and gas scenarios (unit cost for new windows and gas, respectively) are the most influential in the respective cases.

The HP scenario presents a couple of differences, compared to the results for DH and gas. The first difference is the positive sign of the regression coefficient of the HP's lifetime. This is expected, as a high value of the parameter (longer lifetime) results in an increased NPV. In this case, increasing the heat pump's lifetime by 1 σ (3 years) would change the output by a 0.57 standard deviation in the positive direction. The second difference in the HP results is the difference in the relative importance of the five variated parameters.

Contrary to the results for DH and gas, the derived coefficients for the HP have smaller relative differences, entailing an evenly distributed degree of importance of each one. While the least influential parameter is still the electricity unit cost (SCR = −0.303, Table 4), its importance is much greater compared to the scenarios of gas and DH. This is an interesting observation, as the electricity cost in the HP model is lower than the DH and gas models (see Figure 7); however, the increased electrical consumption compensates for the price difference and increases the importance of the parameter. The order for the second, third, and fourth parameters in the HP scenario follows the amount of attic insulation, the unit cost of attic insulation, and PV implementation.

3.3. Global Cost Robustness of the Baseline

The secondary objective of this study is to test the robustness of the identified cost-effective package in [28], applied as a baseline for the sensitivity analyses studies in this paper. The robustness analyses are carried out by comparing the resulting variations of the NPV from the MC method to the NPV of renovation packages obtained in [28].

The comparison for the three energy supply systems is shown in Figure 9, where the grey markers depict packages from [28], while the marker types categorize the packages by their achieved energy savings. Packages 1–6 achieve approximately 20% energy savings, Packages 7 and 8 obtain 40%, and 9 and 10 reach 60% energy savings compared to the pre-renovated energy demand of the case study building. The variations attained by the MC method for the baseline (Package 7) are visualized by the box plots in Figure 9. The mid-line in the box plot marks the median of the output data, while "x" depicts the mean. The box bounds the first and third quartile (interquartile range, meaning 50% of the observations), whereas the whiskers bound the minimum and maximum data values excluding extremes.

A key observation in Figure 9 is a discrepancy in the NPV values of Package 7 from [28] (marked with a black cross) and the baseline values for the studied systems (marked with a horizontal line), even though both models are identical. This is caused by the updated discount rates (DR) from 2018 to 2021. As stated in Section 2, the updated DR are 0.5% points lower than the previously applied values from 2018. As expected and stated in [32], a lower discount factor would result in lower global cost (in this case, the NPV), which is consistent with the results in Figure 9. This leads to the conclusion that the NPV of the different solutions is highly dependent on the DR, which is ultimately a policy decision.

In all three cases, the difference due to the updated DR values is larger than the obtained spread from the variated parameters. In the case of the HP, the change in the DR has a significant effect on the result (1.5 MM EUR), while for DH (0.7 MM EUR) and gas (0.18 MM EUR) the difference is still considerable, although to a smaller extent compared to the HP. This shows that the DR significantly influence which technology will be singled out as cost-optimal. For example, with the DR applied in the analysis in [28] (marked in grey in Figure 9), the HP is not competitive with DH or gas. In contrast, the HP is comparable to the other technologies with the updated DR types; in fact, the HP is the solution with the lowest NPV.

Suppose the difference stemming from updated DR is corrected, so that the NPV of Package 7 and that of the baseline for the represented variations are equal. Nearly all the package solutions with lower energy reduction targets (Package 1–6) fall in the range of box plot whiskers for all three systems. This is logical, as the NPV of most of these packages is within ±5–10% of that of the baseline. Comparing the box plots' interquartile ranges, the number of packages falling within range is reduced to four for DH and gas and two for HP. This indicates that the selection of packages with similar NPVs should be taken with caution as variation in the input may cause the rearrangement of the packages.

On the contrary, the NPV of the packages with similar or higher energy-saving targets than the baseline (Packages 8–10) falls outside the respective box plot's ranges. The higher energy savings in Packages 8–10 are achieved by additional or more expensive renovation actions than the baseline. For DH and gas, the NPV of Packages 8–10 is at least 30% costlier than the baseline, whereas the NPV for the same packages combined with the HP is in the range of 20–30%. This indicates that the cost comparison between solutions with a significant difference in NPVs can be taken with certainty, assuming that the LCC approach for all solutions has been consistent. On the other hand, solutions with similar NPV results are not as certain, and thus decision making in such situations should be approached with caution.

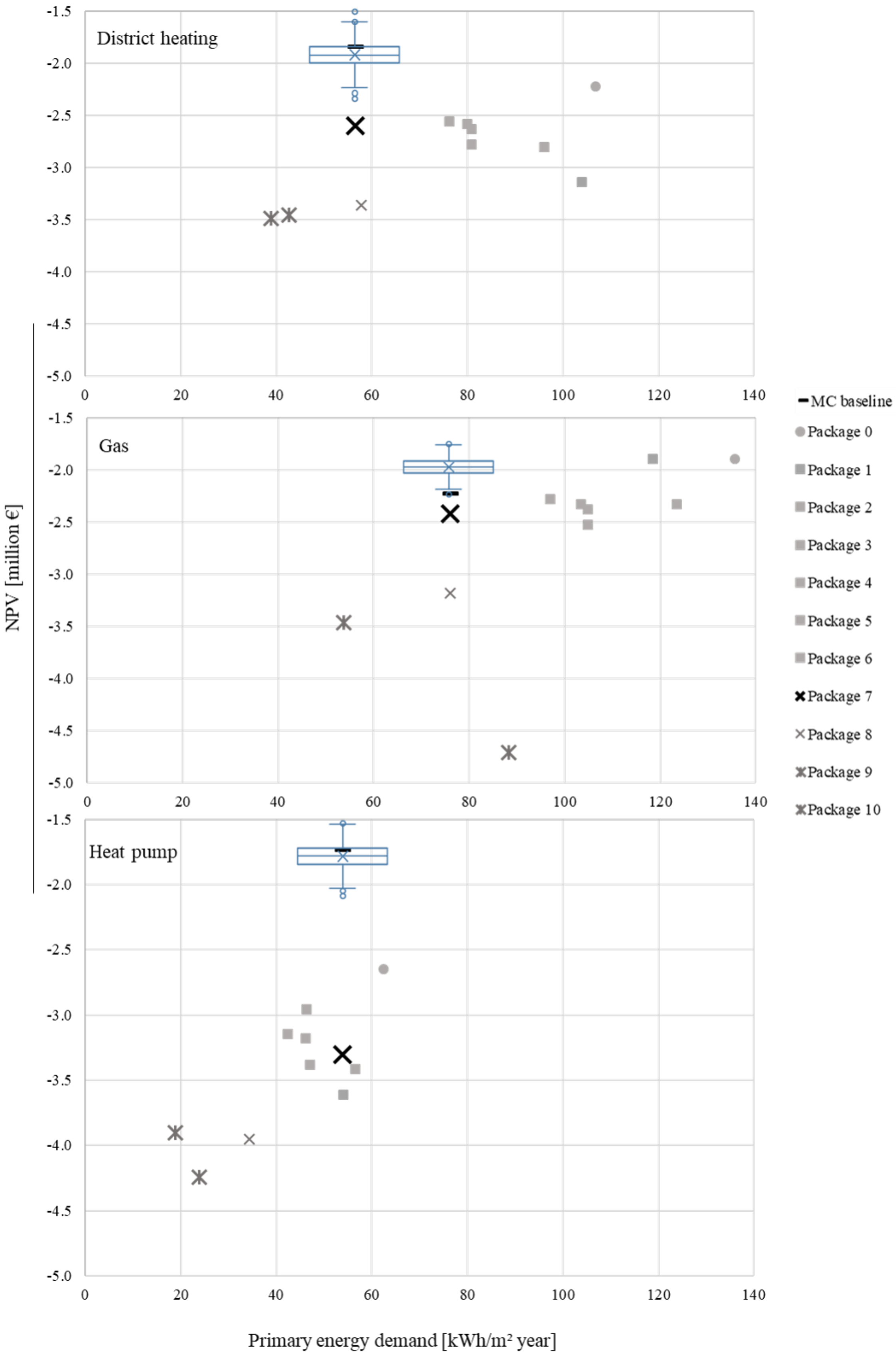


Figure 9. Robustness analyses of the cost-effective baseline (Package 7), compared to cost-optimality results for renovation packages adapted from [28]. Box plot depicts results from Monte Carlo (MC) variation for three energy supply systems.

Overall, the results show that the global LCC is significantly sensitive to DR, whose implementation is ultimately a policy decision. The difference between the results is greatest for the HP and smallest in the case of gas. This is also consistent with the intentions set out in [32]. Moreover, the greater difference for the HP is also compatible with the findings presented in [24], which also suggest, a greater effect of the reduced discount factors for solutions with greater energy savings.

4. Discussion

The analysis presented in this study focuses on economic aspects related to the construction of renovation scenarios, namely, LCC analysis and sensitivity by the OAT and MC variation methods. However, the authors wish to highlight that the composition of the renovation measures should at all times also account for the indoor climate criteria as well as the comfort and safety of the occupants.

The approach used in this paper provides findings that shed light on the importance of different parameters in an LCC calculation, their interaction, and rank of importance. The findings are, however, limited to the scope of the analysis. In this paper, the analysis considers the perspective of a multi-family building owner, disregarding income. For such cases, the income in the LCC calculations can originate from rent, rent increases, selling electricity to the grid, savings of purchased energy from the grid, etc. If one or more of these profits are integrated into an LCC analysis, the results for the influence and relative share of importance for each parameter could change significantly.

The applied combination of local (OAT) and global (MC) methods seemed appropriate, as the OAT approaches are good estimators of sensitivity for linear or nearly linear mathematical models. The linearity of the investigated baseline model (and its variations) was confirmed by the very high R2 values of the multivariate linear regression. It should be noted that the linearity of this (these) model(s) is (are) expected as boundary conditions, and the model inputs are investigated separately. Models where the variation of boundary conditions and inputs are variated simultaneously may prove to be non-linear.

The MC and quasi-random sampling approach is selected due to the ability of covering the solution space comprehensively. This, however, is true when the sample number is sufficient to represent the combinations of variated parameters. A "sufficient" number of samples is typically determined based on the number of variated parameters and investigated variations. The MC simulations at hand are limited to five variation parameters and 5000 samples for each investigated energy system. While this is a relatively low number of samples for a MC simulation, even the coverage of the solution space is assured by the use of Sobol quasi-random sample selection [16]. Moreover, given that the calculation models proved to be linear, a relatively small number of samples may even be sufficient to provide coverage of the solution space. To determine whether the 5000 samples are an adequate number of simulations for the investigated models, the DH baselines were simulated with a different number of samples. The spread in the results is compared in Figure 10 by a histogram depicting the standardized frequency to the sample number. The figure shows that despite the different number of samples, the spread of the results is nearly equal in all cases. Considering the linearity of the model, this result was anticipated. A slight difference is evident for the cases with 100 and 500 input samples, where the distribution differs slightly, but the results' range is still similar to all the other cases.

A growing body of the literature has explored the sensitivity of financial assumptions in LCC calculations, specifically DR and energy price developments [5,20–22,24]. Despite the variety in the applied methods for assessing the sensitivity and scope (the entities considered in the calculation) of the referenced papers, there is a consensus that financial assumptions significantly impact the LCC output. This corresponds well with the findings of this paper, considering the comparability between the OAT-based sensitivity indexes for the boundary conditions and those of the most influencing energy efficiency measures. Even though the interactions of the financial and building-related inputs and their effects on the output are not investigated in this paper, there is a need for further exploration on the matter. This is evident, as the results in [24] showed that financial input parameters alone have interactive effects on the LCC output, representing cost-optimal renovation cases. To the authors' best knowledge, only one study focuses on the sensitivity of both financial and building-related inputs [27]. The study applies MC- and Sobol-sampling methodologies based on sensitivity and uncertainty analysis for the evaluation of economic performance for a range of energy efficiency levels. The findings in [27] regarding the investment cost and a lifetime of the most expensive solution being the most influential for the output are compatible with the results of this paper's HP scenario.

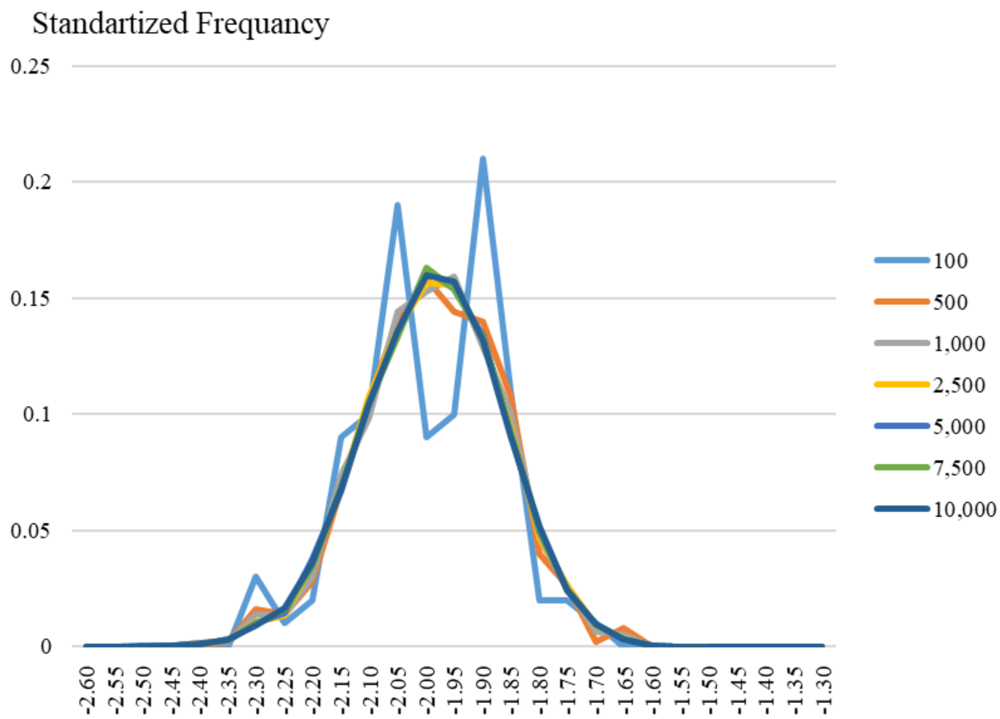


Figure 10. Comparison of the number of simulations.

5. Conclusions

- This study examined the relationship between the input and output of LCC calculations for a pre-selected renovation case of a residential building in Denmark.
- The study sheds light on the currently available data and sources for the inputs required for LCC calculations, focused on renovation expenditures.
- The applied approach consists of one-at-a-time (OAT) and Monte Carlo (MC) methods for the variation of the inputs. A simple first-order sensitivity index was calculated for all the model inputs variated with the OAT method to compare the sensitivity of the parameters and select the most influential ones for further variation with the MC method. The investigation of the interactive effects of the variated parameters on the output was quantified using linear regression and the analysis of the standardized regression coefficients for the selected parameters.
- Performing OAT variation on the boundary conditions and building-related inputs enabled the comparison of the individual effects of the three boundary conditions: the discount rate (DR) type, price development (PD), and calculation period. Based on the results, it can be concluded that the DR type and PD for electricity and district heat have approximately the same effect. At the same time, the variation in the calculation period showed greater sensitivity indexes for the studied scenarios. However, these results should be taken with caution, as they represent the individual effect of each input on the output and not the interactive effects of all inputs.
- The OAT method's results implied a linear relationship between the input and outputs, which was verified by the high R2 values resulting from a regression analysis of the MC

results for all studied models. Furthermore, the applied regression method (Sensitivity-Ranked Regression Coefficients) ranked each of the five variated parameters with respect to the output's sensitivity to each one.

- The financial parameters and calculation period in Denmark can be considered deterministic, as their values are determined by legislation.
- Given that specific values are determined concerning the investigated building type, the variation applied in this paper is aimed at quantifying the expected variance when a different set of boundary condition assumptions is used in the selected baseline. The applied OAT approach to building-related model inputs showed that energy demand-related inputs are the most influential.
- The global sensitivity analysis shows that the calculation models with District Heating (DH) and gas reveal that the most influential inputs are about twice as sensitive as the next most influential ones. In those cases, the relative importance of the parameters of DH and gas is nearly equal, with a slight variation between the ranking in the two cases. On the contrary, for a scenario with a Heat Pump (HP), the lifetime of the HP is determined as the most sensitive. Moreover, the relative difference in the regression coefficient values (importance) for the different parameters in the HP case is much smaller than the DH and gas cases.
- This study adds to the understanding of the relationship between the inputs and output for LCC calculations, considering a cost-effective renovation package combined with three energy supply systems for heating and DHW production.

Author Contributions: Conceptualization, Y.I.A.; methodology, Y.I.A. and M.Z.P.; software, K.T.J.; validation, Y.I.A. and M.Z.P.; formal analysis, Y.I.A.; investigation, Y.I.A.; resources, P.H. and M.Z.P.; data curation, Y.I.A.; writing—original draft preparation, Y.I.A.; writing—review and editing, Y.I.A.; visualization, Y.I.A.; supervision, M.Z.P. and P.H.; project administration, M.Z.P. and P.H.; funding acquisition, P.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

NZEB	Nearly Zero Energy Building
EU	European Union
LCC	Life Cycle Cost
OAT	One-at-a-time
MC	Monte Carlo
HP	Heat Pump
DHW	Domestic Hot Water
DH	District Heating
PV	Photovoltaic
GC	Global Cost
NPV	Net Present Value
DR	Discount Rate
PD	Price Development
TDC	Technology Data Catalogue
DEA	Danish Energy Agency
IR	Interest Rate
SA	Sensitivity Analysis
SRRC	Standardized Rank Regression Coefficient
SI	Sensitivity Index
PDF	Probability Density Function

CDF	Cumulative Distribution Function
CO	Cost type
Δy_i	Difference between the output values obtained from the minimum and maximum variated input value of parameter *i*
bi	Regression coefficient
σ	Standard deviation
µ	Mean
CO_{INIT}	Initial cost
CO_a	Annual cost
CO_{CO_2}	Emission cost
$CO_{fin(TSL)}$	Disposal cost
VALe5	Residual value
D_f	Discount factor
t_{TC}	Calculation period.
RAT	(i) price evolution of parameter i-

Appendix A

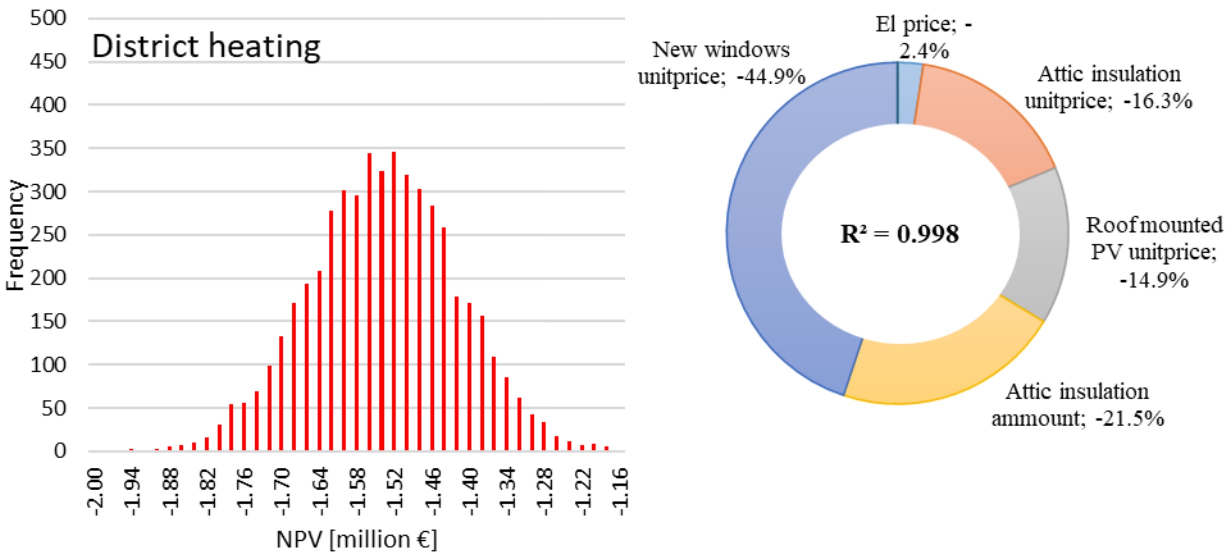


Figure A1. Left: histogram representation of resulting NPV for low district heating unit cost. Right: resulting share of regression coefficients and R^2 value of the linear approximation.

Table A1. Regression parameters for calculation model with District Heating. Regressions for all three cost levels of DH are identical.

Parameter x_i	**New Windows**	**Attic Insulation**	**Roof-Mounted PV**	**Attic Insulation**	**Electricity**	**ε**
Attribute	unit price	Amount	Unit price	Unit price	Unit price	
Coefficients	−0.82258	−0.393233267	−0.27311281	−0.29911744	−0.04455671	-4.15×10^{-16}
Standard error values of coefficients	0.000643	0.000642742	0.000642742	0.000642742	0.000642742	0.000642741
R^2	0.997937	0.045448669	#N/A	#N/A	#N/A	#N/A
Regression—sum of squares	483,126.4	4994	#N/A	#N/A	#N/A	#N/A
Residual sum of squares	4989.684	10.31551425	#N/A	#N/A	#N/A	#N/A

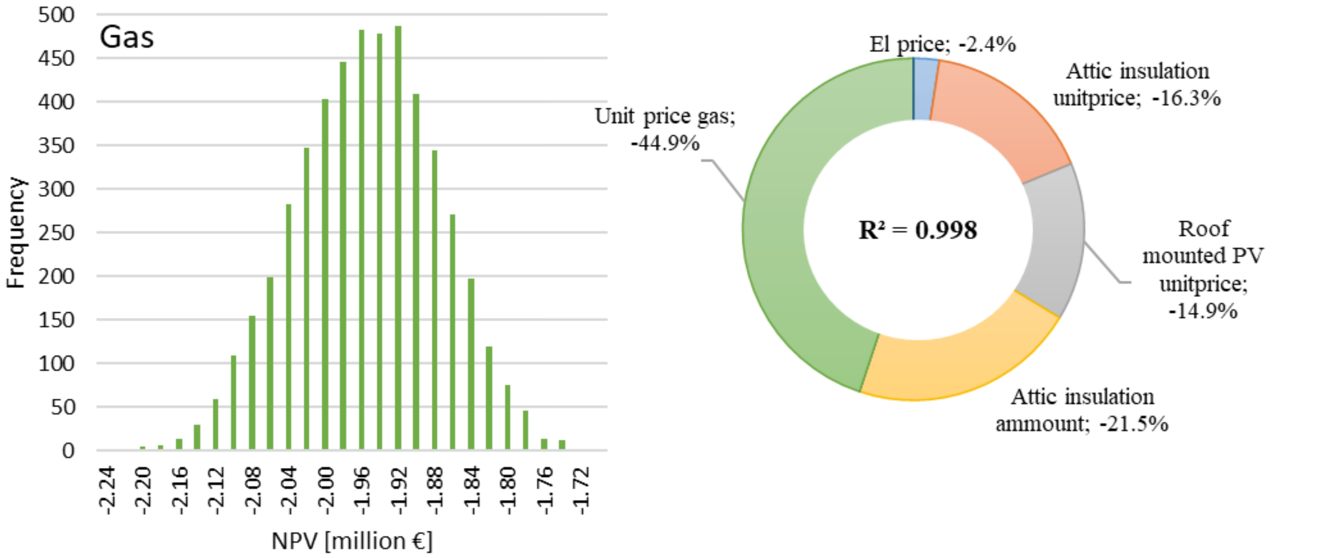


Figure A2. Left: histogram representation of resulting NPV for gas. Right: resulting share of regression coefficients and R^2 value of the linear approximation.

Table A2. Regression parameters for calculation model with gas.

Parameter x_i	Gas	Attic Insulation	Roof-Mounted PV	Attic Insulation	Electricity	ε
Attribute	unit price	Amount	Unit price	Unit price	Unit price	
Coefficients	−1.2292	−0.587637	−0.408132	−0.44699	−0.06658	5.561
Standard error values of coefficients	0.00096	0.000960	0.000960	0.000960	0.000960	0.00096
R^2	0.997937	0.067917	#N/A	#N/A	#N/A	#N/A
Regression—sum of squares	483,126.4	4994	#N/A	#N/A	#N/A	#N/A
Residual sum of squares	11142.74	23.0361	#N/A	#N/A	#N/A	#N/A

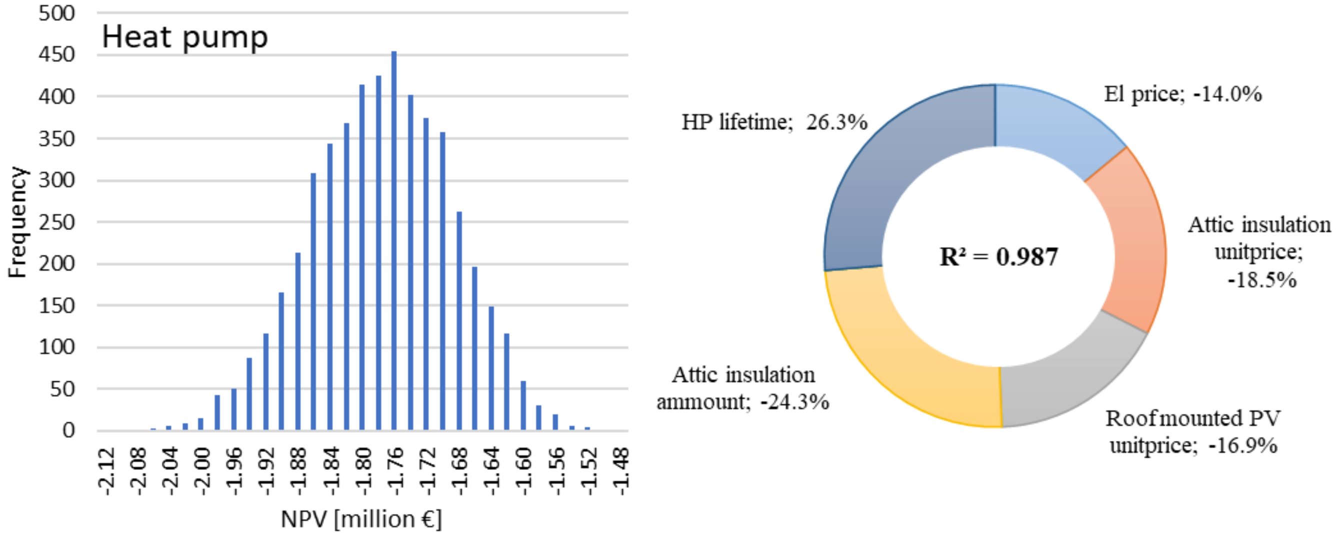


Figure A3. Left: histogram representation of resulting NPV for heat pump. Right: resulting share of regression coefficients and R^2 value of the linear approximation.

Table A3. Regression parameters for calculation model with heat pump.

Parameter x_i	Heat Pump	Attic Insulation	Roof-Mounted PV	Attic Insulation	Electricity	ε
Attribute	Lifetime	Amount	Unit price	Unit price	Unit price	
Coefficients	0.57032	−0.525506908	−0.365908376	−0.39981676	−0.30338984	-1.12×10^{-14}
Standard error values of coefficients	0.001635	0.001634858	0.001634856	0.001634856	0.001634857	0.00163
R^2	0.986652	0.115601688	#N/A	#N/A	#N/A	#N/A
Regression—sum of squares	73,830.49	4994	#N/A	#N/A	#N/A	#N/A
Residual sum of squares	4933.261	66.73856858	#N/A	#N/A	#N/A	#N/A

References

1. European Commission. Directive (EU) 2018/2002 of the European Parliament and of the Council of 11 December 2018 Amending Directive 2012/27/EU on energy efficiency. *Off. J. Eur. Union* **2018**, *328*, 210–230.
2. European Union. Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency. *Off. J. Eur. Union* **2018**, *156*, 75–91.
3. Bolig og Planstyrrelsen. Available online: https://baeredygtighedsklasse.dk/ (accessed on 10 September 2022).
4. Ministry of the Interior and Housing. Available online: https://im.dk/Media/637602217765946554/National_Strategy_for_Sustainable_Construktion.pdf (accessed on 10 September 2022).
5. Ferreira, M.; Almeida, M.; Rodrigues, A. Cost-optimal energy efficiency levels are the first step in achieving cost-effective renovation in residential buildings with a nearly-zero energy target. *Energy Build.* **2016**, *133*, 724–737. [CrossRef]
6. Congedo, P.M.; D'Agostino, D.; Baglivo, C.; Tornese, G.; Zacà, I. Efficient Solutions and Cost-Optimal Analysis for Existing School Buildings. *Energies* **2016**, *9*, 851. [CrossRef]
7. Morrissey, J.; Horne, R. Life cycle cost implications of energy efficiency measures in new residential buildings. *Energy Build.* **2011**, *43*, 915–924. [CrossRef]
8. Sağlam, N.G.; Yılmaz, A.Z.; Becchio, C.; Corgnati, S.P. A comprehensive cost-optimal approach for energy retrofit of existing multi-family buildings: Application to apartment blocks in Turkey. *Energy Build.* **2017**, *150*, 224–238. [CrossRef]
9. *DS/EN 15459-1:2017*; Energy Performance of Buildings—Economic Evaluation Procedure for Energy Systems in Buildings—Part 1: Calculation Procedured, Module M1—14. European Committee for Standartization: Brussels, Belgium, 2017.
10. Giuseppe, E.D.; Massi, A.; D'Orazio, M. Impacts of Uncertainties in Life Cycle Cost Analysis of Buildings Energy Efficiency Measures: Application to a Case Study. *Energy Procedia* **2017**, *111*, 442–451. [CrossRef]
11. Burhenne, S.; Tsvetkova, O.; Jacob, D.; Henze, G.P.; Wagner, A. Uncertainty quantification for combined building performance and cost-benefit analyses. *Build. Environ.* **2013**, *62*, 143–154. [CrossRef]
12. Janssen, H. Monte-Carlo based uncertainty analysis: Sampling efficiency and sampling convergence. *Reliab. Eng. Syst. Saf.* **2013**, *109*, 123–132. [CrossRef]
13. Heiselberg, P.; Brohus, H.; Hesselholt, A.; Rasmussen, H.; Seinre, E.; Thomas, S. Application of sensitivity analysis in design of sustainable buildings. *Renew. Energy* **2009**, *34*, 2030–2036. [CrossRef]
14. Wei, T. A review of sensitivity analysis methods in building energy analysis. *Renew. Sustain. Energy Rev.* **2013**, *20*, 411–419. [CrossRef]
15. Østergård, T.; Jensen, R.L.; Maagaard, S.E. Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis. *Energy Build.* **2017**, *142*, 8–22. [CrossRef]
16. Østergård, T.; Jensen, R.L.; Mikkelsen, F.S. The best way to perform building simulations? One-at-a-time optimization vs. Monte Carlo sampling. *Energy Build.* **2020**, *208*, 109628. [CrossRef]
17. Ruparathna, R.; Hewage, K.; Sadiq, R. Economic evaluation of building energy retrofits: A fuzzy based approach. *Energy Build.* **2017**, *139*, 395–406. [CrossRef]
18. La Fleur, L.; Rohdin, P.; Moshfegh, B. Investigating cost-optimal energy renovation strategies for a multifamily building in Sweden. *Energy Build.* **2019**, *203*, 109438. [CrossRef]
19. Guardigli, L.; Bragadin, M.A.; Della Fornace, F.; Mazzoli, C.; Prati, D. Energy retrofit alternatives and cost-optimal analysis for large public housing stocks. *Energy Build.* **2018**, *166*, 48–59. [CrossRef]
20. Pallis, P.; Gkonis, N.; Varvagiannis, E.; Braimakis, K.; Karellas, S.; Katsaros, M.; Vourliotis, P.; Sarafianos, D. Towards NZEB in Greece: A comparative study between cost optimality and energy efficiency for newly constructed residential buildings. *Energy Build.* **2019**, *198*, 115–137. [CrossRef]
21. Pallis, P.; Gkonis, N.; Varvagiannis, E.; Braimakis, K.; Karellas, S.; Katsaros, M.; Vourliotis, P. Cost effectiveness assessment and beyond: A study on energy efficiency interventions in Greek residential building stock. *Energy Build.* **2019**, *182*, 1–18. [CrossRef]
22. Liu, L.; Rohdin, P.; Moshfegh, B. LCC assessments and environmental impacts on the energy renovation of a multi-family building from the 1890s. *Energy Build.* **2016**, *133*, 823–833. [CrossRef]

23. Sandberg, N.H.; Sartori, I.; Vestrum, M.I.; Brattebø, H. Using a segmented dynamic dwelling stock model for scenario analysis of future energy demand: The dwelling stock of Norway 2016–2050. *Energy Build.* **2017**, *146*, 220–232. [CrossRef]
24. Hamdy, M.; Sirén, K.; Attia, S. Impact of financial assumptions on the cost optimality towards nearly zero energy buildings—A case study. *Energy Build.* **2017**, *153*, 421–438. [CrossRef]
25. Ascione, F.; Bianco, N.; De Stasio, C.; Mauro, G.M.; Vanoli, G.P. CASA, cost-optimal analysis by multi-objective optimisation and artificial neural networks: A new framework for the robust assessment of cost-optimal energy retrofit, feasible for any building. *Energy Build.* **2017**, *146*, 200–219. [CrossRef]
26. Gonzalez-Caceres, A.; Karlshøj, J.; Vik, T.A.; Hempel, E.; Nielsen, T.R. Evaluation of cost-effective measures for the renovation of existing dwellings in the framework of the energy certification system: A case study in Norway. *Energy Build.* **2022**, *264*, 112071. [CrossRef]
27. Di Giuseppe, E.; Iannaccone, M.; Telloni, M.; D'Orazio, M.; Di Perna, C. Probabilistic life cycle costing of existing buildings retrofit interventions towards nZE target: Methodology and application example. *Energy Build.* **2017**, *144*, 416–432. [CrossRef]
28. Antonov, Y.I.; Heiselberg, P.K.; Pomianowski, M.Z. Novel Methodology toward Nearly Zero Energy Building (NZEB) Renovation: Cost-Effective Balance Approach as a Pre-Step to Cost-Optimal Life Cycle Cost Assessment. *Appl. Sci.* **2021**, *11*, 4141. [CrossRef]
29. Antonov, Y.I.; Heiselberg, P.; Flourentzou, F.; Pomianowski, M.Z. Methodology for Evaluation and Development of Refurbishment Scenarios for Multi-Story Apartment Buildings, Applied to Two Buildings in Denmark and Switzerland. *Buildings* **2020**, *10*, 102. [CrossRef]
30. Aalborg University. *LCCbyg*; Aalborg University: Copenhagen, Denmark, 2020.
31. Danish Ministry of Finance. *Den Samfundsøkonomiske Diskonteringsrente*; Finance Minister: Copenhagen, Denmark, 2019.
32. Danish Ministry of Finance. *Dokumentationsnotat—Den Samfundsøkonomiske Diskonteringsrente*; Danish Ministry of Finance: Cophenhagen, Denmark, 2021; pp. 1–19.
33. *Energistyrelsens Prisdatabase 2019*; Danish Energy Agency: Copenhagen, Denmark, 2019.
34. Danish Energy Agency and Energinet. *Technology Data for Individual Heating Plants*; Danish Energy Agency and Energinet: Copenhagen, Denmark, 2016.
35. Danish Energy Agency. *Technology Data for Energy Plants for Electricity and District Heating Generation*; Danish Energy Agency: Copenhagen, Denmark, 2019; pp. 1–374.
36. MOLIO Price Database. Available online: https://www.molio.dk/emner/oekonomi-og-kalkulation/prisdata (accessed on 10 September 2022).
37. Aagaard, N.-J.; Brandt, E.; Aggerholm, S.; Haugbølle, K. *Levetider af Bygningsdele ved Vurdering af Bæredygtighed og Totaløkonomi*; SBI Forlag: Copenhagen, Denmark, 2013; ISBN 978-87-563-1586-9.
38. *Elforsyningens Nettariffer & Priser pr. 1. Januar 2019*; Dansk Energi: Viby, Denmark, 2019.
39. *Samfundsøkonomiske Beregningsforudsætninger for Energipriser Og Emissioner, Oktober 2019*; Danish Energy Agency: København, Denmark, 2019.