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A Novel Approach to Determine Multi-Tiered Nearly Zero-Energy Performance Benchmarks Using Probabilistic Reference Buildings and Risk Analysis Approaches

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Abstract: The Energy Performance of Buildings Directive (EPBD) mandates European Union Member States (MS) to conduct cost-optimal studies using the national calculation methodology (NCM), typically through non-calibrated asset-rating software. Nearly zero-energy building (NZEB) levels must be derived for each chosen Reference Building (RB), which are generally defined using deterministic parameters. Previous research proposed an innovative cost-optimal method that replaces 'non-calibrated deterministic RBs' with 'probabilistically Bayesian calibrated reference building (RB)' to better handle building stock uncertainties and diversities when deriving benchmarks. This paper aims to develop a framework to address two research gaps necessary for the successful application of the innovative cost optimal method: (1) providing objective criteria for defining NZEB benchmarks and (2) propagating uncertainties and financial risk for each defined benchmark. A robust approach for defining NZEB benchmarks according to four different ambition levels (low, medium, high, and highest) was developed by objectively considering distinct points from multiple cost-optimal plots employing different financial perspectives. Risk analysis is then performed for each defined benchmark by propagating risk from the posterior calibration parameter distributions to visualize and statistically quantify the financial risk, including robust risk, that the private investor could face for reaching each derived benchmark ambition level. The innovative cost-optimal methodology that incorporates the developed framework was applied to a hotel RB case study. The results showed that the developed framework is capable of deriving distinct benchmarks and quantitatively uncovering the full financial risk levels for the four different renovation ambition levels. The current cost-optimal method was also performed for the hotel case study with the RB defined determinitically and using the non-calibrated NCM software, SBEM-mt v4.2c. It was found that the financial feasibility and energy-saving results per benchmark are significantly more realistic and transparent for the proposed innovative cost-optimal method including a better match between the simulated and metered energy consumption with a difference of less than 1% in annual performance. Thus, the performance gap between calculated and actual energy performance that is synonymous with the EPBD methodology, as reported in the literature, is bridged. The case study also showed the importance of the risk analysis. Performing the cost-optimal analysis for a Bayesian calibrated RB using the mean value of the posterior calibrated parameter distributions without propagating uncertainty produced highly optimistic results that obscured the real financial risk for achieving the higher ambition levels of the NZEB benchmarks. Consequently, the developed framework demonstrated a time-bound tightening approach to achieve higher energy performance ambitions, improve risk transparency to private investors, and facilitate more targeted policies towards a net zero-carbon status. Thus, the proposed method considering parameter uncertainty and calibrated RBs is instrumental for devising robust policy measures for the EPBD, to achieve a realistic and long-lasting sustainable energy goal for European buildings.

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1. Introduction

In its efforts to achieve the decarbonization of buildings by 2050, the European Commission (EC) has updated the Energy Performance of Buildings Directive (EPBD) in 2010. The directive requires European Union Member States (MS) to carry out cost-optimal studies using the national calculation methodology (NCM) generally via non-calibrated asset-rating software. The methodology takes into account deterministic combinations of energy efficiency measures (COMs) together with their different market price development (PD) and discount rate (DR) scenarios to determine the minimum energy performance requirements for buildings and the nearly zero-energy building (NZEB) levels using the cost-optimal method described in [1,2]. One of the main aims is to accelerate the deep renovation of existing building stocks.

Despite the positive push enabled by the EPBD, Gatt et al. [3,4] and Gatt [5] explained how the use of 'non-calibrated deterministic Reference Buildings (RBs)' in the cost-optimal method has led to many limitations critical to successful policy making (a deterministic RB model is defined as a building energy model with a single set of input parameter values for the envelope and technical building systems for a building stock category under study. In addition, the calibration of RB energy models with building stock metered operational EP data is not undertaken). Such limitations include the resulting large energy performance (EP) gaps recorded throughout Europe between measured and simulated data (refer to [6–16]) and the inability to comprehensively validate the chosen RBs without the use of metered operational energy performance data. Moreover, the effect of uncertainties or building stock diversity in the RB input parameters for calculating cost-optimal and NZEB level benchmarks is not taken into account. As a result of these limitations, the current cost-optimal approach may not provide sufficient confidence that the proposed cost-optimal measures or the NZEB levels and the derived Energy Performance Indicators (EPIs) themselves are realistic and economically feasible and whether the desired energy savings and carbon neutrality targets are ultimately achieved when implementing them in practice.

To counteract these limitations, Gatt et al. [3] and Gatt [5] proposed an update to the EPBD cost-optimal method that applies 'probabilistic Bayesian calibrated RBs' to replace 'non-calibrated deterministic RBs' as applied in state-of-the-art Urban Building Energy Modeling (UBEM) studies, including [17–23]. The aim is to better handle parameter uncertainty and building stock diversity by defining the uncertain parameters of an RB building energy model as a probability distribution called 'priors', reflecting the current knowledge of the parameter values. The defined 'prior' distributions of the most significant parameters are then updated to narrower posterior distributions using Bayesian calibration that incorporates Bayes' theorem and metered energy performance data. Once RB calibration is performed and validated, as detailed in Gatt et al. [3], to meet the requirements of the EPBD, NZEB EP benchmarks need to be derived through a cost-optimal analysis by plotting Energy Performance (EP) of the calibrated RB against the global Life Cycle Costs (LCC) for different combinations of energy efficiency measures (COMs). For robust policy making, the final step of the novel proposed cost-optimal method then involves conducting a probabilistic risk analysis in operational energy savings and life cycle financial feasibility for an RB energy model under study to meet each defined NZEB EP benchmark. The steps and full motivation behind the novel proposed EPBD cost-optimal method applying 'probabilistic Bayesian calibrated RBs' in comparison to the current 'deterministic' EPBD cost-optimal method is detailed in Gatt et al. [3] and Gatt [5].

In the context of NZEB benchmarking, as explained in the review by Gatt et al. [24] and D'Agostino et al. [25,26] regarding the state-of-the-art in different NZEB definitions, the process of objectively establishing NZEB EP benchmarks, even when considering the current 'deterministic' EPBD cost-optimal method, is not straightforward. This difficulty arises from the fact that the term 'Nearly' in NZEB is not a quantifiable metric, and the European Commission (EC) does not provide objective criteria for defining NZEB benchmarks once cost-optimal plots, which consider the influence of different Discount Rates (DRs) and Price Development (PD) scenarios, are constructed.

Furthermore, to ensure that the risk analysis complies with the EPBD cost-optimal method requirements described by the EC [1], one must consider the joint impact of technical and financial uncertainties on the NZEB EP benchmarks. More specifically, it is necessary to apply both a financial and macroeconomic perspective to LCC and perform a Sensitivity Analysis (SA) on the impact of different DRs and PD scenarios on the resulting EP benchmarks for a RB. In addition, the propagated uncertainty in EP improvements and LCC risks for a defined NZEB benchmark level generated from the 'Bayesian calibrated RBs' for the proposed EPBD cost-optimal approach requires to be visualized, statistically quantified and interpreted to facilitate the application of more robust energy support policies.

This paper will tackle these research gaps for the novel proposed EPBD cost-optimal method detailed in Gatt et al. [3] and Gatt [5]. This is completed by developing and validating a two-stage framework that objectively derives NZEB benchmarks according to different levels of EP ambition and performs a risk analysis for each of them in line with the EPBD. The developed framework is then applied to a Bayesian calibrated RB case study implementing the novel proposed EPBD cost-optimal method. For comparison purposes, the cost-optimal method is also performed for the case study using the current approach, which employs a deterministic, non-calibrated RB.

More specifically, this research will aim to answer the following research questions:

- How can NZEB benchmarks in terms of EP ambition levels for a RB be effectively defined using a harmonized and ordinal scale approach?
- What methods can be employed to quantify and propagate both EP and financial uncertainties associated with each identified ambition level for a RB, with the aim of informing the development of robust energy renovation support policies?
- How does the proposed EPBD cost-optimal approach better handle uncertainties when deriving cost-optimal NZEB measures and benchmarks versus the current EPBD approach?
- How can the proposed EPBD cost-optimal approach devise more robust energy renovation support policies under different levels of ambition to meet the required renovation targets?

This research paper is organized as follows. Section 2 details the proposed two-stage framework methodology. To demonstrate the developed two-stage framework, Section 3 applies the framework to a five-star hotel RB EnergyPlus model case study that has already undergone Bayesian calibration in Gatt [5]. Section 4 will then compare, from a statistical and policy perspective, the results and outcomes of the proposed novel EPBD cost-optimal approach incorporating the proposed two-stage framework with the current 'deterministic' approach. To enable this comparison, the current (deterministic) EPBD cost-optimal approach will be applied to the hotel RB case study modeled using the non-calibrated SBEM-mt software v4.2c [27], the NCM for Malta. In Section 5, the above research questions will be answered. The RB case study will facilitate the answering of the above research questions by evaluating the novel EPBD cost-optimal approach, incorporating the proposed framework, in comparison to the current deterministic cost-optimal approach. This evaluation aims to assess the potential of the novel EPBD cost-optimal approach to better enable EU policymakers to devise more robust energy renovation support policies and to facilitate the path for the EU to achieve its carbon neutrality goals by 2050.

2. The NZEB EP Benchmarking and Probabilistic Risk Analysis Framework for the EPBD Cost-Optimal Method

The proposed two-stage framework methodology implementing NZEB EP benchmarking and risk analysis is visually shown in Figure 1 and is described in this section.

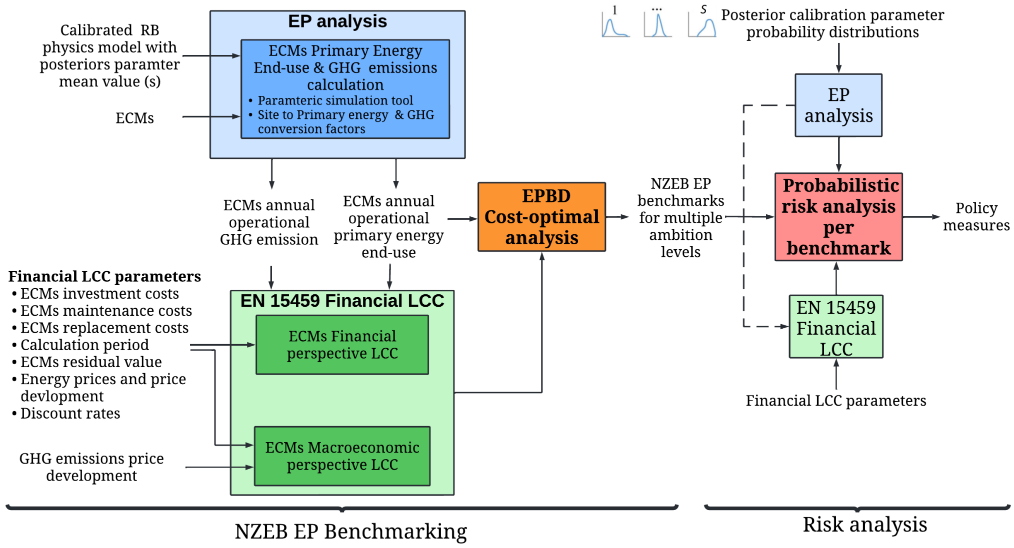


Figure 1. Flowchart detailing the approach used in this study to establish NZEB benchmarks and perform a risk analysis per benchmark.

2.1. NZEB EP Benchmarking Approach to Different Ambition Levels

The proposed NZEB EP benchmarking approach applies the mean value of the posterior distributions of the calibration parameters to each RB building physics energy model representing a building stock under study, as shown in Figure 1. The calibrated RB model characterized by the mean value of the posterior distributions of the calibration parameters is treated deterministically when deriving EP benchmarks to facilitate the NZEB benchmarking process and make it more objective. The cost-optimal EP and NZEB EP benchmarks are then derived using the EPBD cost-optimal analysis that applies a set of packages of energy efficiency measures (COMs) and calculates the annual primary energy consumption and EN 15459 [28] global LCC for each COM using the current EPBD cost-optimal methodology. The main inputs to calculate the EP and global LCC required for the EPBD cost-optimal analysis are shown in Figure 1.

The global LCC, $C_g(t)$ for a COM, referred to the starting year t_0, over the calculation period t, is calculated by summing the different costs incurred, for every energy efficiency measure j constituting the COM and discounting them to the starting year t_0 by means of a discount factor R_d as follows [2]:

$$C_g(t) = CO_{INIT} + \sum_j \left[\sum_{i=1}^{t} (CO_{a,i}(j).R_d(i)) + CO_{carbon,i}(j) - VAL_{fin,t}(j) \right] \quad (1)$$

where:

- CO_{INIT} is the initial investment costs;
- $CO_{a,i}$ is year i annual cost, which is the addition of the running costs and periodic (including annual maintenance costs $CO_{a,maint}$) or replacement costs $CO_{a,RAR}$. This cost is discounted by the discount factor R_d, during every year i;
- $CO_{carbon,i}$ is the carbon (GHG emissions) cost for every year i resulting from the operational energy consumption;
- $VAL_{fin,t}$ is the residual value discounted to the starting year t_0.

R_d (i) for year i is related to the DR, r, as:

$$R_d(p) = \left(\frac{1}{1 + r/100}\right)^p \tag{2}$$

where p means the years quantified from the starting period.

Equation (1) details the macroeconomic global LCC calculation that considers each cost without taxes and charges. For the financial global LCC calculation, the cost of Greenhouse (GHG) emissions is not considered and all costs include taxes and charges [2].

The EPBD cost-optimal analysis generates the cost-optimal plots as their main output to establish minimum EP requirements for benchmarking. According to the EPBD Commission Regulation [1,2], the cost-optimal analysis requires to be carried out both from a macroeconomic and financial perspective, and an SA is mandatory to identify the impact of different PD scenarios and DRs on the resulting cost-optimal and NZEB benchmarks. The NZEB benchmarking approach considered in this research directly uses this requirement to objectively define ordinal levels of NZEB EP benchmarks according to different EP ambition levels. More specifically, the approach defines four different levels of NZEB EP ambition levels to complement the current subjective EPBD NZEB definition, which are derived by considering the resulting cost-optimal plots for all perspectives and sensitivities as follows:

1. **Low ambition**: The EP corresponding to the financial scenario that gives the lowest global LCC when compared to the reference scenario, for the DRs and PD sensitivities considered.
2. **Medium ambition**: The least ambitious EP when choosing between scenarios 1 and 2. Scenarios 1 and 2 are defined in the paragraph below.
3. **High ambition**: The most ambitious EP when choosing between scenarios 1 and 2. Scenarios 1 and 2 are defined in the paragraph below.
4. **Highest ambition**: The EP coinciding with the macroeconomic sensitivity scenario giving the best EP in the macroeconomic feasibility region of the cost-optimal plots for the DRs and PD sensitivities considered.

For the above NZEB EP definitions, Scenario 1 and Scenario 2 are defined as follows:

- **Scenario 1**: The EP arising from the financial perspective that provides the 'best' EP in the feasibility region of the financial cost-optimal plots for the DRs and PD sensitivities considered. This can be viewed as the theoretically 'best' EP that private investors are willing to invest in without benefiting from financial incentives.
- **Scenario 2**: The EP corresponding to the macroeconomic scenario that gives the lowest global LCC compared to the reference scenario for the DRs and PD sensitivities considered. Private investors will not likely invest in this EP level unless financial incentives are made available and provided that this EP also falls within the feasibility region of the financial cost-optimal plots.

To demonstrate the benchmarking approach, a generic cost-optimal analysis that considers plots four sensitivity combinations for PD and DR for both the financial and macroeconomic perspectives is shown in Figure 2 for a fictitious RB. In the figure, each blue point on the plots represents a COM, and the black dashed lines for each cost-optimal plot show the 'operational' EP scenario. The four NZEB EP ambition levels for an RB under study are visually depicted as points A, B, C, and D in Figure 2. As an example, the ambition levels are demonstrated for the 'operational' (metered) EP is shown by the vertical line, and the corresponding global LCC is depicted by the horizontal line. The EP scenario for the calibrated RB before the application of energy efficiency measures, termed the 'reference' scenario, should coincide as closely as possible with the 'operational' EP scenario for a calibrated model.

Furthermore, the application of a COM that is found below the horizontal black dashed line for each plot in Figure 2 provides a lower global LCC than the 'operational' scenario, and its application is, therefore, feasible for the PD and DR under consideration. Following this context and the above definitions, point A coincides with the lowest NZEB EP ambition in Figure 2. At the same time, Scenario 1 and Scenario 2 are represented by point B and point C, respectively. For the specific context of Figure 2, point C coincides with the medium NZEB EP ambition level, while point B coincides with the high EP ambition. Furthermore, the highest NZEB EP ambition level coincides with point D.

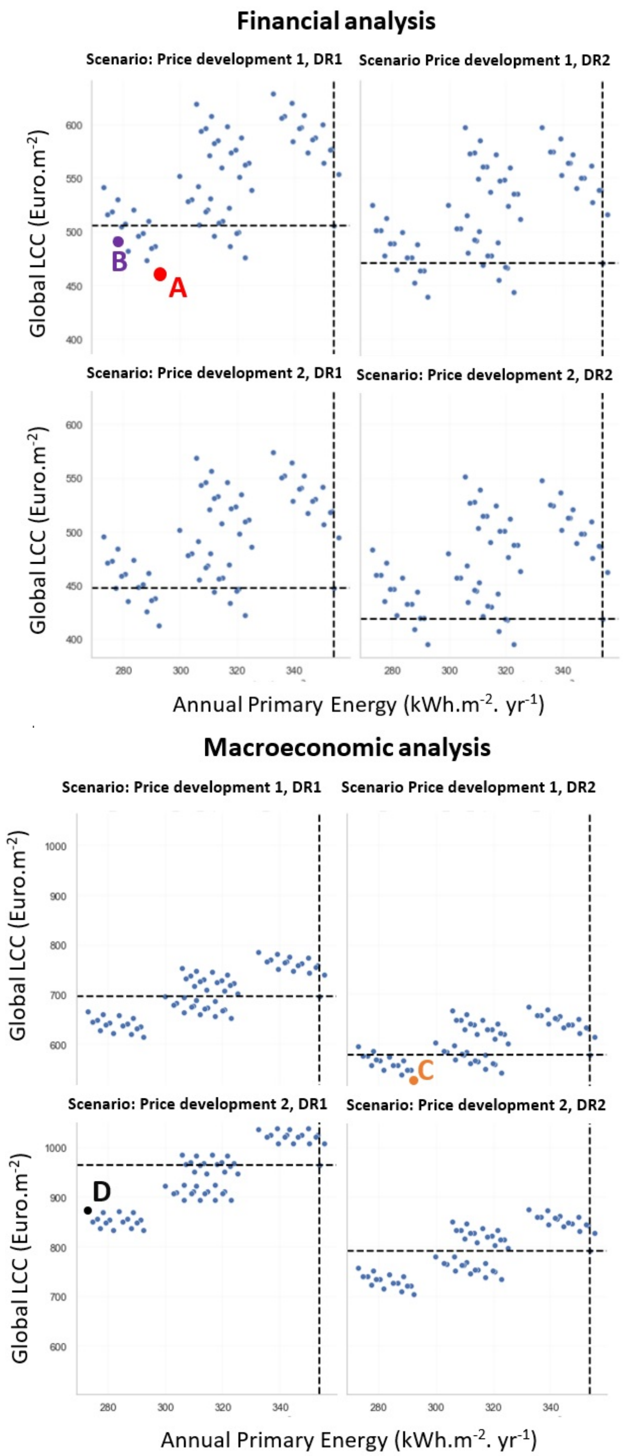


Figure 2. The four NZEB EP benchmarks visually depicted using the cost-optimal plots that consider both the financial and macroeconomic LCC perspectives and different sensitivities for the PD and DRs.

From the cost-optimal plots, one can also deterministically quantify the financial risk experienced by a private investor to upgrade an RB to each NZEB EP ambition level benchmark. This risk quantification, termed the 'deterministic financial risk' in this paper, is simply the difference between the global LCC of the reference scenario and the global LCC corresponding to each level of NZEB ambition under study for a considered financial analysis scenario. This risk can be easily calculated within the current deterministic EPBD cost-optimal analysis framework.

An advantage of defining the above multiple-objective NZEB benchmarks according to different ambition levels is that it supports the aim for determining an objective and time-bound tightening approach [29] to NZEB EP benchmarking. This prepares the market to adapt over time to more stringent EP requirements and allows MS to establish a long-term path so that policymakers are able to continuously improve the EP of their building stock [30]. For a holistic and integrated design approach [31,32] to NZEB, multiple objective NZEB benchmarks can also be derived for each requirement of the multiple indicator NZEB assessment approach provided in Annex H of ISO 52000-1 [33]. This approach was applied for a case study building in Gatt et al. [24]. The ISO 52000-1 [33] standard defines four sequential requirements which are to be met for a building to qualify for NZEB status. The requirements first prioritize the building's passive design in terms of "The building Fabric (Energy needs)", followed by energy-efficient technical building systems in terms of "The total primary energy use", and finally gives weighting renewable energy generation to offset the energy demand and reduce the carbon footprint of the building. Renewable energy generation is reflected in terms of the third requirement, i.e., "Non-renewable primary energy use without compensation between energy carriers", and the final NZEB rating, i.e., "Numerical indicator of non-renewable primary energy use with compensation".

2.2. Probabilistic Risk Analysis for Each Defined NZEB Benchmark

For the risk analysis shown in Figure 1, the posterior calibrated parameter probability distributions are used to define the calibrated RB building physics model. For each defined NZEB EP ambition level found from the NZEB EP benchmarking approach, uncertainty in operational EP and the corresponding LCC is propagated for the RB building physics model implementing the corresponding combination of energy efficiency measures (COM) that achieves the desired NZEB EP ambition level under study. To enable this propagation in uncertainty for each NZEB ambition level, a near-random sample is generated from the posterior calibrated parameter probability distributions using the Latin Hypercube (LHS) sampling method. The RB building physics model characterized with the COM that achieves the NZEB ambition level under study is then run for each sample point to calculate the annual operational EP required to derive the life cycle operational energy cost for the defined energy prices, PD and DR according to the EN 15459 [28] LCC calculation. The resulting operational energy cost for each sample point is then combined with the other defined financial LCC parameters shown in Figure 1 to calculate the other EN 15459 [28] LCC that makes up the total global LCC. The main output from the uncertainty propagation for each NZEB ambition level is a dataset consisting of the annual operational EP and the corresponding total global LCC for each sample point.

For a comprehensive risk analysis in line with the EPBD Commission regulation [2], the above uncertainty propagation for a defined NZEB ambition level must calculate the EN 15459 [28] financial LCC considering sensitivities for different PD scenarios and DRs. A risk analysis that considers the macroeconomic perspective to LCC is not considered mandatory for this step, given that the main objective is to establish policies that objectively and more realistically quantify financial support measures that reduce risk to the private investor to reduce the technical and financial uncertainty barriers. These are the main barriers to energy renovation [34–36] and EP contracting [37], to facilitate the transition of the building stock to the established EP benchmarks. For quantifying risk, the uncertainty in operational EP and global LCC for each defined NZEB ambition level and each sensitivity must then be compared against the 'Reference' or 'as is' scenario of not implementing energy efficiency measures. The latter is performed by propagating uncertainty for the calibrated RB building physics model without energy efficiency measures for an LHS sample space of the posterior calibrated parameter probability distributions.

In this framework, joint plots [38] (also called joint grids [39] or marginal plots [40]) are proposed to visualize the EP and financial risk for achieving an NZEB ambition level. These plots facilitate the combination of bi-variate scatter plots with marginal uni-variate probability distributions. The scatter plots analyze the correlation between the global LCC and the annual primary energy for the uncertainty propagation. In addition, the marginal probability density plots on the top and right margin of the scatter plot show the distribution of annual primary energy and global LCC along both axes. Figure 3 shows plots for a fictitious calibrated RB for the purpose of demonstrating the proposed joint plot construction that can be implemented for this stage of the cost-optimal method for an NZEB ambition level that has four PD and DRs combination scenarios. Figure 3 uses different colors to distinguish between the uncertainty propagation from the 'reference' scenario and NZEB ambition level under consideration for both the annual primary energy and global LCC. For this framework, the joint plots shown in Figure 3 need to be constructed for all NZEB ambition levels defined in Section 2.1.

From the joint plots shown in Figure 3, policymakers can perform various data analysis techniques to identify policy options to facilitate the transition of building stocks to a defined NZEB EP ambition level. For a given PD and DR scenario, financial risk is eliminated in theory for the private investor when the global LCC probability density plots for the 'reference' scenario and the NZEB ambition level under study do not intersect each other. An objective and statistical approach to policymaking to calculate the worst-case or 'robust' [41] financial risk is, therefore, to establish a % HDI, typically 89% or 95% HDI [42], to identify the points that cover most of the distribution for the global LCC for both the ambition level under consideration and the 'reference' scenario density plots. The robust financial risk is the quantification of the global LCC that causes the HDI credible interval of the density plots to intersect with each other.

To visualize, demonstrate, and provide a mathematical context to robust financial risk, Figure 4 shows a typical joint plot for a defined ambition level for a specific DR and PD combination scenario. The marginal distribution plot for the financial global LCC is magnified, and the density plot for both the 'reference' and NZEB ambition level scenarios are described in terms of the upper and lower bounds of a % HDI credible interval that covers most of the distribution. From Figure 4, the robust global LCC financial risk that causes the intersection between the two credible intervals is calculated as shown in Equation (3):

$$Robust\ LCC\ financial\ risk\ (\text{euro.m}^{-2}) = Amb\_HDI\_upper - Ref\_HDI\_lower \quad (3)$$

where Amb_HDI_upper is the upper bound of the HDI credible interval ambition level distribution under study, and Ref_HDI_lower is the lower bound of the 'reference' scenario distribution credible interval. This calculation can be performed for each DR and PD under consideration to identify the impact of varying these financial parameters on the robust global LCC financial risk for each defined NZEB ambition level in Section 2.1 to ensure well-informed policy decision making under uncertainty.

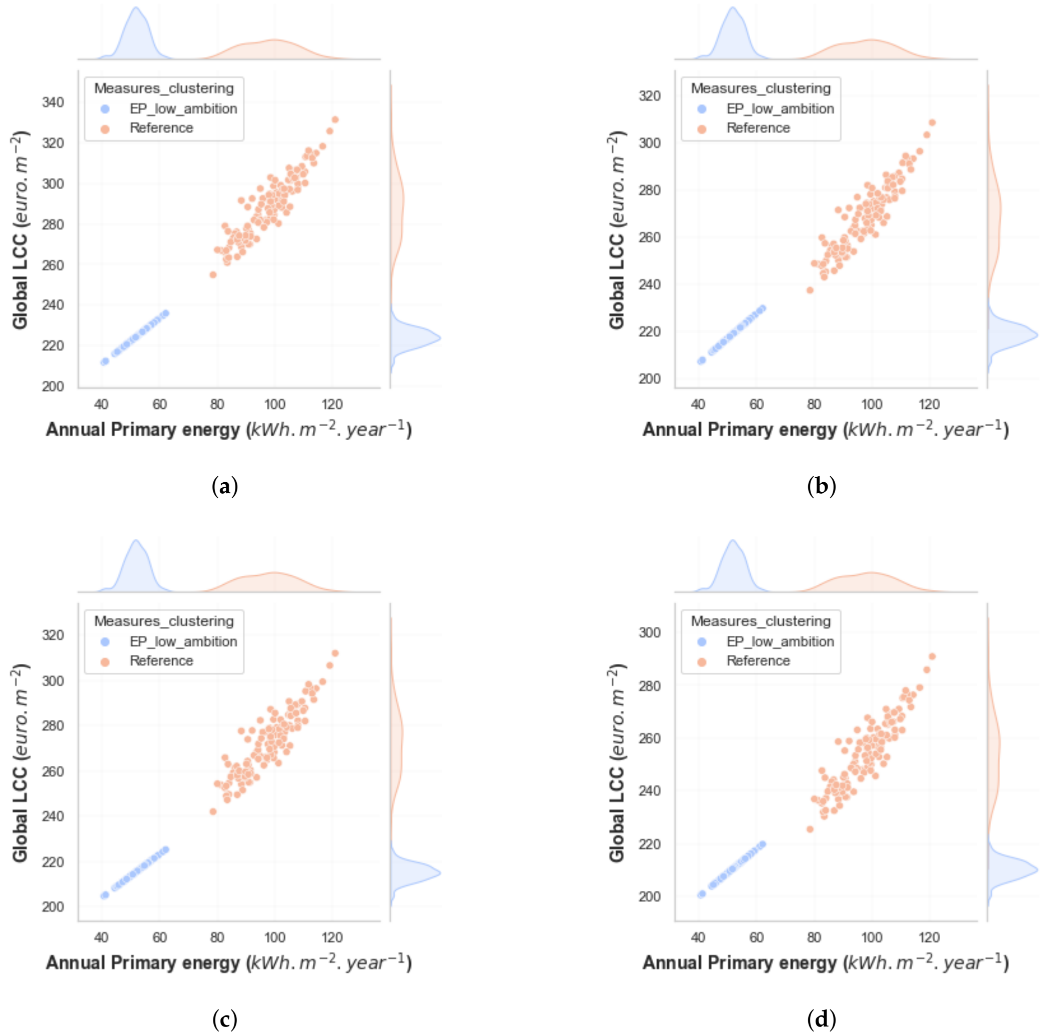


Figure 3. Joint plots combining scatter plots with probability distributions to analyze operational EP and financial global LCC uncertainty of a package of measures corresponding to an NZEB benchmark versus the 'reference' scenario. (**a**) Scenario: Price dev. 1, DR 1; (**b**) Scenario: Price dev. 1, DR 2; (**c**) Scenario: Price dev. 2, DR 1; (**d**) Scenario: Price dev. 2, DR 2.

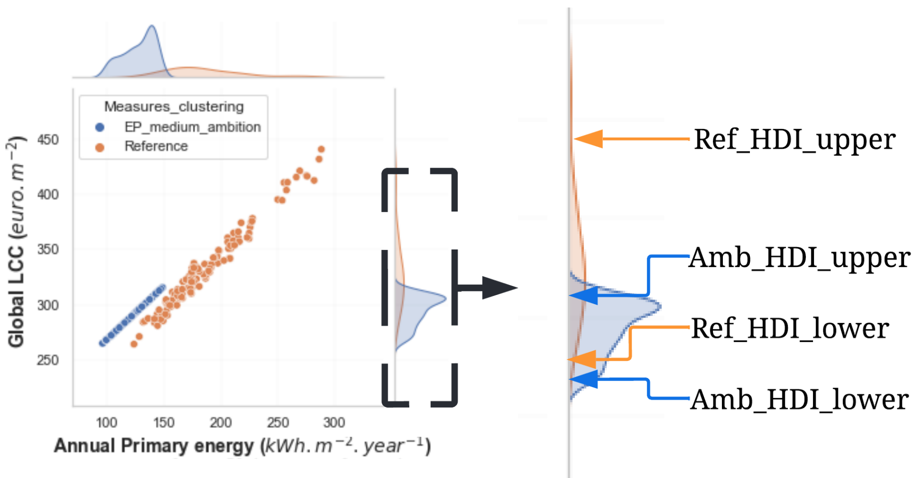


Figure 4. Joint plot visualizing the uncertainty propagation for a defined NZEB ambition level versus the 'reference' scenario visualizing the parameters to calculate the robust global LCC financial risk at a given DR and PD scenario for well-informed policy making to facilitate the transition of a building to NZEB.

3. Hotel Case Study Employing a 'Probabilistic Bayesian Calibrated' Method to Undertake the Proposed Cost-Optimal Approach

This section applies the NZEB EP benchmarking and probabilistic risk analysis framework described in Section 2 to a 'probabilistic Bayesian calibrated' hotel RB case study energy model described in Gatt [5] to undertake the proposed cost-optimal approach. The selected RB is a typical five-star hotel building in Malta, identified using the machine learning approach developed and detailed in Gatt [5]. This innovative approach defines RBs for a 'small' multi-functional building stock (a 'small' building stock is one where the number of explanatory variables '*X*' impacting EP is greater than the number of building observations '*N*' in a population or sample under study).

The identification of parameters for calibration involved conducting a Sensitivity Analysis using the Morris Method [43]. Subsequently, Bayesian Calibration was executed using monthly metered consumption data for electricity and light fuel oil (LFO). In order to mitigate computational intensity, a meta-model for electricity and LFO replaced the more computationally intensive RB EnergyPlus model. To calibrate the parameters, a matrix derived from field-observed input data was combined with a matrix from computer simulation data, following the methodology outlined in Higdon et al. [44], and in accordance with the guidelines established by Chong et al. [45]. Detailed information on the Sensitivity Analysis, the definition and selection of priors, and the implementation of calibration in Stan [46], including the corresponding code, can be found in Gatt [5].

3.1. NZEB EP Benchmarking Applied to the RB Case Study

For the proposed EPBD NZEB EP benchmarking approach described in Section 2.1, the building EnergyPlus (physics) model is treated deterministically by applying the mean value of the calibration parameters posterior distributions. The calibration parameters posterior distributions are shown in Appendix A for Domestic Hot Water (DHW) fueled by LFO and Appendix B for the electricity uses. These distributions are replicated from Gatt [5].

3.1.1. Energy Conservation Measures (ECMs) Considered for the Case Study

The passive and building energy systems (active) ECMs for the EPBD cost-optimal method used to derive NZEB EP benchmarks are shown in Tables 1 and 2, respectively. In total, three passive ECMs were considered, MP1 to MP3. MP1 is the application of external wall insulation, MP2 is the addition of roof insulation, and MP3 is the application of a spectrally selective film to the glazing fenestration. As shown in Table 1, the application of insulation improves the U-value or thermal transmittance of the components of the building envelope under study, while the spectrally-selective film is applied to reduce the heat gain from solar radiation. For each ECM, MP1 to MP3, two discrete options or parameter values were investigated. The two options are the initial parameter values and the final parameter values after the application of the respective ECMs.

Table 1. Passive measures considered for the hotel case study.

Measure	Initial Parameter Values	Measures Description	Final Parameter Values
MP1	Wall U-value = 2.1 W.m^{-2}.K^{-1}	Application of 5 cm XPS on external walls	Wall U-value = 0.5 W.m^{-2}.K^{-1}
MP2	Roof U-value = 1.7 W.m^{-2}.K^{-1}	Application of 8 cm EPS on roof	Roof U-value = 0.4 W.m^{-2}.K^{-1}
MP3	Glazing U-value = 3.1 W.m^{-2}.K^{-1}, SHGC = 0.7, Light transmission = 0.8	Application of 3M corporation PR70 film on fenestration glazing	Glazing U-value = 3 W.m^{-2}.K^{-1}, SHGC = 0.4, Light transmission = 0.5

Similarly, three building energy systems (active) ECMs, MA1 to MA3, were considered for NZEB EP benchmarking, as shown in Table 2. MA1 upgrades the existing Variable Refrigerant Flow (VRF) system to improve its rated Coefficient of Performance (COP) in both heating and cooling, MA2 replaces the Domestic Hot Water (DHW) boiler with a DHW heat pump, and MA3 improves the Specific Fan Power (SFP) of the mechanical ventilation system. Furthermore, ECMs MA1 to MA3 each investigate two discrete options for NZEB EP. More specifically, the mean value of the calibration parameter posterior distributions describes the initial values, while the final parameter values follow the application of ECMs.

Table 2. Building energy systems (active) measures considered for the hotel case study.

Measure	Initial Parameter Values for NZEB EP Benchmarking	Initial Parameter Values for Risk Analysis	Measures Description	Final Parameter Values
MA1	VRF rated cooling COP = 2.18, VRF rated heating COP = 3.4	VRF rated cooling COP posterior distribn, VRF rated heating COP = 3.4	Upgrade/RAR air-cooled VRF system	VRF rated cooling COP = 4.2, VRF rated heating COP = 4.31
MA2	DHW boiler heater efficiency = 0.84	DHW boiler heater efficiency posterior distribn	RAR fuel boiler with DHW heat-pump	DHW heat pump rated COP = 4
MA3	Mech vent system fan pressure rise = 1112 Pa	Mech vent system fan pressure rise posterior distribn	Upgrade/RAR mechanical vent system	Mech vent system fan pressure rise = 945 Pa

3.1.2. EN 15459 Global LCC Financial Parameters

For the case study, the values of the global LCC financial parameters for each ECM and the corresponding 'reference' scenario of not implementing ECM are shown in Tables 3 and 4, for the building envelope (passive) and building energy systems (active) ECMs, respectively. The DRs considered for the financial calculation are DR 1 of 3.2%, to reflect the average landing rate in October 2021 in Malta [47], and a further sensitivity (DR 2) of 4%, which reflects the financial DR recommended by EC to be used as a reference for the long-term real opportunity cost of capital for the programming period 2014–2020 [48]. Furthermore, the values of the global LCC macroeconomic parameters for the ECMs are the same as for the financial calculations, but the 18% VAT is deduced from the costs. The DR chosen for macroeconomic calculation are DR 1 of 3% according to the EC guidelines [2] and a further sensitivity (DR 2) of 5% reflecting the 2018 cost-optimal studies for Malta [49]. The calculation period for both financial and macroeconomic calculations is taken to be 20 years, as required by the EC guidelines [2] for commercial buildings. The period starting from the year 2022 to the year 2042 was considered for the case study.

For the development of the price for the fuel and carbon emissions costs, two scenarios are considered, PD 1 and a further sensitivity, PD 2. PD 1 considers the future price escalation trend to follow the same % annual average EU linear PD rate of the past years. In contrast, PD 2 considers future price escalations based on EU outlook studies or machine learning regression prediction trends based on a time series of previous observations.

Table 3. Financial global LCC parameters for the passive ECMs considered for the hotel case study.

Passive ECM	CO_{INIT} (euro.m^{-2}) [b]	$CO_{a,maint}$ (% of CO_{INIT})	Life Time (Years)	$CO_{a,RAR}$ (euro)	Year of RAR	VAL_{fin} [c] (euro.m^{-2})
Reference scenario [a]	0	0	0	0	0	0
MP1	45	0	30	0	0	15
MP2	70	0	30	0	0	23
MP3	106	10	30	0	0	35

[a] Scenario when no ECMs are applied. [b] Area in m^2 refers to the surface area of the building element on which the passive ECM is applied. For the case study, the wall area for MP1 is 19,796 m^2, the roof area for MP2 is 19,825 m^2, and the glazing area for MP3 is 4476 m^2. [c] Non-discounted VAL_{fin} values shown.

Table 4. Financial global LCC parameters for the building energy systems (active) ECMs considered for the hotel case study.

Active Measure	CO_{INIT} (euro.m^{-2})	CO_{INIT} (euro)	$CO_{a,maint}$ (% of CO_{INIT})	$CO_{a,maint}$ (euro)	Lifetime (years)	$CO_{a,RAR}$ [d] (euro)	Year of RAR	VAL_{fin} [e] (euro)
MA1	136	4,130,025	2	82,061	15	4,130,025	15	2,735,350
Reference_MA1 [a]				205,151				
MA2		649,000	2	12,980	15	649,000	15	432,667
Reference_MA2 [b]				25,960	20	519,200	10	259,600
MA3	94	3,338,429	4	135,377	15	3,338,429	15	2,256,286
Reference_MA3 [c]				169,221				

[a] Reference_MA1 refers to the reference scenario of operating using the current VRF system throughout the calculation period. The cost of operating with this scenario is fully reflected in the $CO_{a,maint}$, which considers the replacement of the system to be spread over 20 years. [b] Reference_MA2 refers to the reference scenario of operating using the current DHW boiler system that has a 10 year remaining lifetime. The DHW boiler system is replaced after 10 years with a similar DHW boiler system having a 20 years lifespan. [c] Reference_MA3 refers to the reference scenario of operating using the current mechanical ventilation system throughout the calculation period. The cost of operating with this scenario is fully reflected in the $CO_{a,maint}$, which considers the replacement of the system to be spread over 20 years. [d] No learning rate is assumed. [e] Non-discounted VAL_{fin} values are shown.

More specifically, for PD 1, the following fuel prices were considered for the global LCC calculation period:

- An increase in the electricity price of 2.5% per year reflects the development of the EU annual average electricity price between 2008 and the first half of 2021 according to the Eurostat electricity price statistics [50].
- An increase in the LFO price of 5% per year to reflect the development of the EU annual average LFO price between 1998 and 2018 according to the European Environmental Agency [51].
- An increase in the price of carbon emissions by 27% per year to reflect the development of the price of carbon emissions allowances between 2005 and the end of 2021 documented on the Trading Economics website [52] for the EU ETS.

As for PD 2, the following fuel prices were considered for the global LCC calculation period:

- Development of electricity prices according to the POTEnCIA central scenario EU energy outlook for 2050 [53]. This scenario depicts stable electricity prices up to 2040 (the electricity generation cost trend up to 2050 is depicted in Figure 107 of [53]).
- Development of LFO prices according to the POTEnCIA central scenario EU energy outlook for 2050 [53]. This scenario depicts an increase in LFO electricity prices of approximately 4% per annum up to 2040 (the LFO cost trend up to 2050 is depicted in Figure 9 of [53]).
- Carbon emissions price forecast using a statistical regression trend developed from a time series of monthly carbon emission price observations between 2007 and 2021 that was collected from the investing.com website [54] for EU ETS. The trend of exponential regression analysis that provides a R^2 of 0.85 is shown in Figure 5. The carbon prices for the months considered in the calculation period, that is, between the period 2022 to 2042, were forecast using this regression model. The prices were then converted to annual resolution data using pivot tables in Microsoft Excel.

Thus, NZEB EP benchmarking for the case study was performed for the following four financial perspective sensitivity scenarios:

1. Scenario A_f: PD 1, DR 1 (3.2%);
2. Scenario B_f: PD 1, DR 2 (4%);
3. Scenario C_f: PD 2, DR 1 (3.2%);
4. Scenario D_f: PD 2, DR 2 (4%).

The same was performed for the following four macroeconomic perspective sensitivity scenarios:

1. Scenario A_m: PD 1, DR 1 (3%);
2. Scenario B_m: PD 1, DR 2 (5%);
3. Scenario C_m: PD 2, DR 1 (3%);
4. Scenario D_m: PD 2, DR 2 (5%).

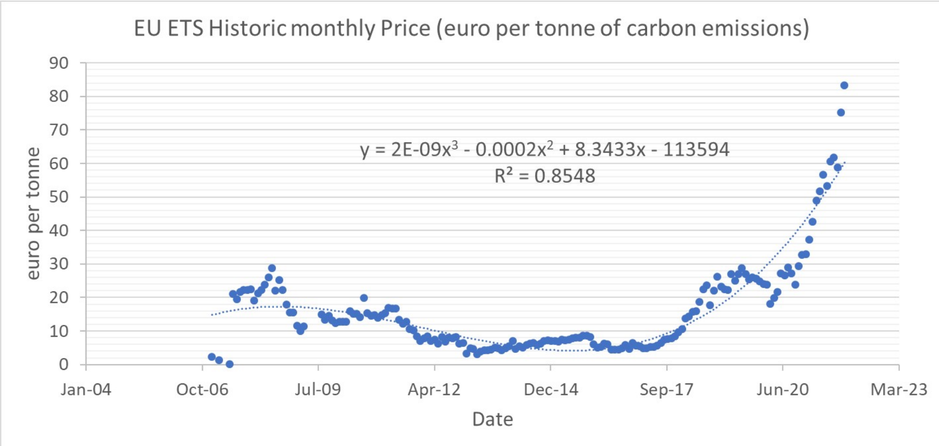


Figure 5. Time series of carbon emission monthly price observations between 2007 and 2021 collected from the website investing.com [54] for the EU ETS. The exponential regression analysis exponential trend provides an R^2 of 0.85.

3.1.3. Cost-Optimal Plots

When combined, the six ECMs in total in Tables 1 and 2, each defined with two discrete options, will define a complete parametric solution of 64 (2^6) cases (COMs). The EP in terms of annual primary energy consumption per square meter of floor area for each of the 64 COMs for the hotel RB case study was determined in EnergyPlus using JEPlus [55] Parametric simulation tool for the weather files and hotel occupancy under consideration, i.e., 2017 to 2019. Testing for more than one year was carried out to demonstrate the robustness of the approach. The EP output for each COM for each year was then fed into the EN 15459 [28] global LCC Equation (1) together with the financial parameters described in Section 3.1.2 above to calculate the global LCC for each COM and perform the cost-optimal analysis by plotting primary energy (kWh/m^2/year) versus global LCC (euro/m^2).

This cost-optimal analysis was carried out for each sensitivity scenario, Scenario A_f to Scenario D_f and Scenario A_m to Scenario D_m, described in Section 3.1.2 above to produce the visualization layout shown in Figure 2 and derive the four levels of NZEB EP benchmarks detailed in Section 2.1 and their corresponding COM for each year.

The analysis was also performed with the hotel occupancy of 2018 and the 2010 weather file. The latter analysis is described with the notation 'year 2018-10'. The year 2018 was chosen because it provides the median hotel annual occupancy between 2017 and 2019, while the NCM software for Malta (SBEM-mt [27]) software uses the weather file for the year 2010 for the EP calculations. Thus, the results from 'year 2018-10' allow a direct comparison with the outcome of the current non-calibrated EPBD cost-optimal approach in Section 4 using SBEM-mt [27], the NCM software for Malta. For the year 'year 2018-10', the operational energy consumption was derived from 2018 operational energy consumption using the variable base temperature degree days method [56], as shown in [5].

Table 5 shows the results for the four different NZEB ambition benchmark levels for each year considered. It can be seen that the ECMs, marked with an X in the table, which makes up the COM required to achieve the four NZEB benchmark ambition levels, are the same for all years. The EP benchmark values for each respective ambition level defined in

$kWh.m^{-2}.year^{-1}$ are also stable, and their sensitivity to weather and occupancy patterns for the years under consideration is minimal. The NZEB EP benchmark values obtained for each respective ambition level for the years considered can also be visualized in Figure 6.

Furthermore, as also shown in Table 5, the potential percentage of energy savings calculated from the reference scenario is also stable throughout the years and varies between 17.45 and 19.36% for the low-ambition benchmark and between 22.90 and 24.72% for the highest ambition benchmark. The resulting potential energy savings from the different COMs achieving each benchmark are consistent with other studies. More specifically, given Malta's temperate climate, the potential for EP improvements by upgrading the building from medium to higher NZEB EP benchmarks through more stringent passive ECMs are not significant when compared to the EP improvements that can be achieved by upgrading the building energy (active) systems. This was shown in various studies, including [24,49,57,58].

Table 5. Derived NZEB EP benchmarks are corresponding ECMs for the hotel case study for 2017 to 2019.

Year	NZEB EP Benchmark Level	Primary EP Benchmark ($kWh.m^2.year^{-1}$)	% EP Improvement	Passive ECMs			Active ECMs		
				MP1	MP2	MP3	MA1	MA2	MA3
2017	Reference	354							
	Operational	355							
	Low	292	17.45				x	x	
	Medium	282	20.46				x	x	x
	High	274	22.50	x	x		x	x	x
	Highest	273	22.90	x	x	x	x	x	x
2018	Reference	357							
	Operational	355							
	Low	289	19.04				x	x	
	Medium	278	22.04				x	x	x
	High	272	23.79	x	x		x	x	x
	Highest	270	24.27	x	x	x	x	x	x
2018_10	Reference	348							
	Operational	349							
	Low	284	18.39				x	x	
	Medium	273	21.55				x	x	x
	High	268	22.99	x	x		x	x	x
	Highest	266	23.56	x	x	x	x	x	x
2019	Reference	365							
	Operational	362							
	Low	294	19.36				x	x	
	Medium	284	22.29				x	x	x
	High	277	24.19	x	x		x	x	x
	Highest	275	24.72	x	x	x	x	x	x

Table 5 also shows that the EP gap between the annual simulated EP for the EnergyPlus model without ECMs (termed the 'reference scenario') and the annual operational metered primary EP is negligible for all considered years. This result clearly highlights the importance of calibrating the RB energy model to obtain realistic EP benchmarks and to enable accurate quantification of primary energy savings when upgrading buildings to the defined NZEB EP benchmark levels.

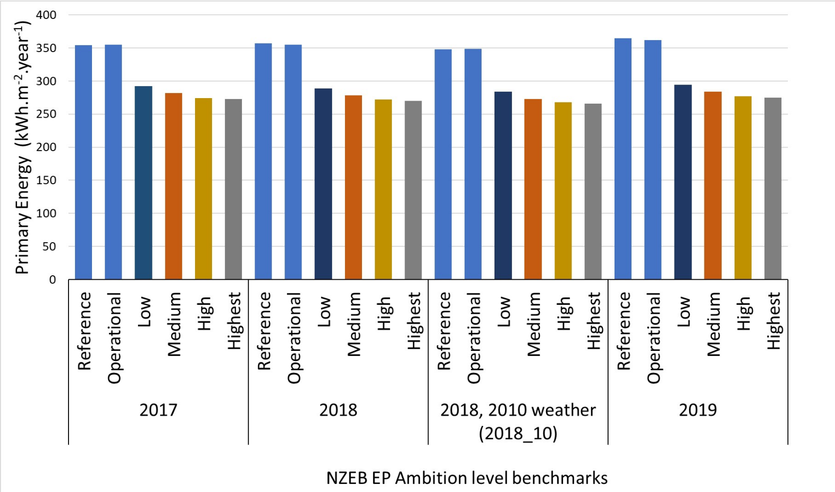


Figure 6. The NZEB primary EP benchmark results for 2017 to 2019.

The resulting cost-optimal plots showing the derived NZEB benchmarks in Table 5 are shown in Figure 7 for the year 2018_10. Using the same notation as in Section 2.1, point A coincides with COM giving the lowest NZEB EP ambition level, point B and point C are the COMs giving the high and medium NZEB EP ambition levels, respectively, while point D is the COM providing the highest NZEB EP ambition level. The resulting cost-optimal plots for the other considered years provided a similar outcome.

3.2. Risk Analysis for Each Defined NZEB Benchmark

This section applies the proposed EPBD probabilistic risk analysis described in Section 2.1 to the hotel RB case study. The risk analysis is performed for each of the four NZEB EP ambition levels considering the time period 2017 to 2019. For this analysis, the hotel EnergyPlus model case study was treated probabilistically with the calibration parameters defined according to the posterior distributions of the calibration parameters shown in Appendices A and B.

The main inputs required to perform the risk analysis are the financial LCC parameters defined in Section 3.1.2, and the uncertainty distribution in operational EP derived from the posterior calibrated parameter probability distributions for each of the derived NZEB EP ambition levels under study and for the 'Reference' scenario. The uncertainty EP propagation exercise was carried out using the LHS sampling method in JEPlus [55].

The joint plots that visualize the EP and financial risk to upgrade to each defined NZEB ambition level when compared with the 'reference' scenario for the low, medium, high, and highest ambition levels are shown in Figures 8–11, respectively, for the year 2018_10. The joint plots for the years 2017, 2018, and 2019 are not shown but provide a similar outcome. Four joint plots are constructed for each ambition level, which is one plot for each financial perspective scenario considered, Scenario A_f to Scenario D_f. The x-axis for each joint plot shows the operational primary energy use per m^2 of floor area. It must be noted that the operational primary energy on each plot only considers the energy end-uses impacted by the COM that is implemented to achieve the required NZEB ambition level (As an example, the x-axis for the joint plots for the NZEB low ambition level depicts the annual operational primary energy per m^2 of floor area for DHW, space heating, and cooling given that measures MA1 and MA2 improve the EP for these energy end-uses. For the other ambition levels, the x-axis for the joint plots also includes the operational primary energy end-use per m^2 for mechanical ventilation. The reason is that, unlike the lower ambition level, the other (higher) ambition levels also implement measure MA3 that improves the EP for mechanical ventilation). In addition, the y-axis for each joint plot depicts the global LCC corresponding to the energy end uses under study. The global LCC robust financial risk is determined by Equation (3) for each ambition level and corresponding joint plots.

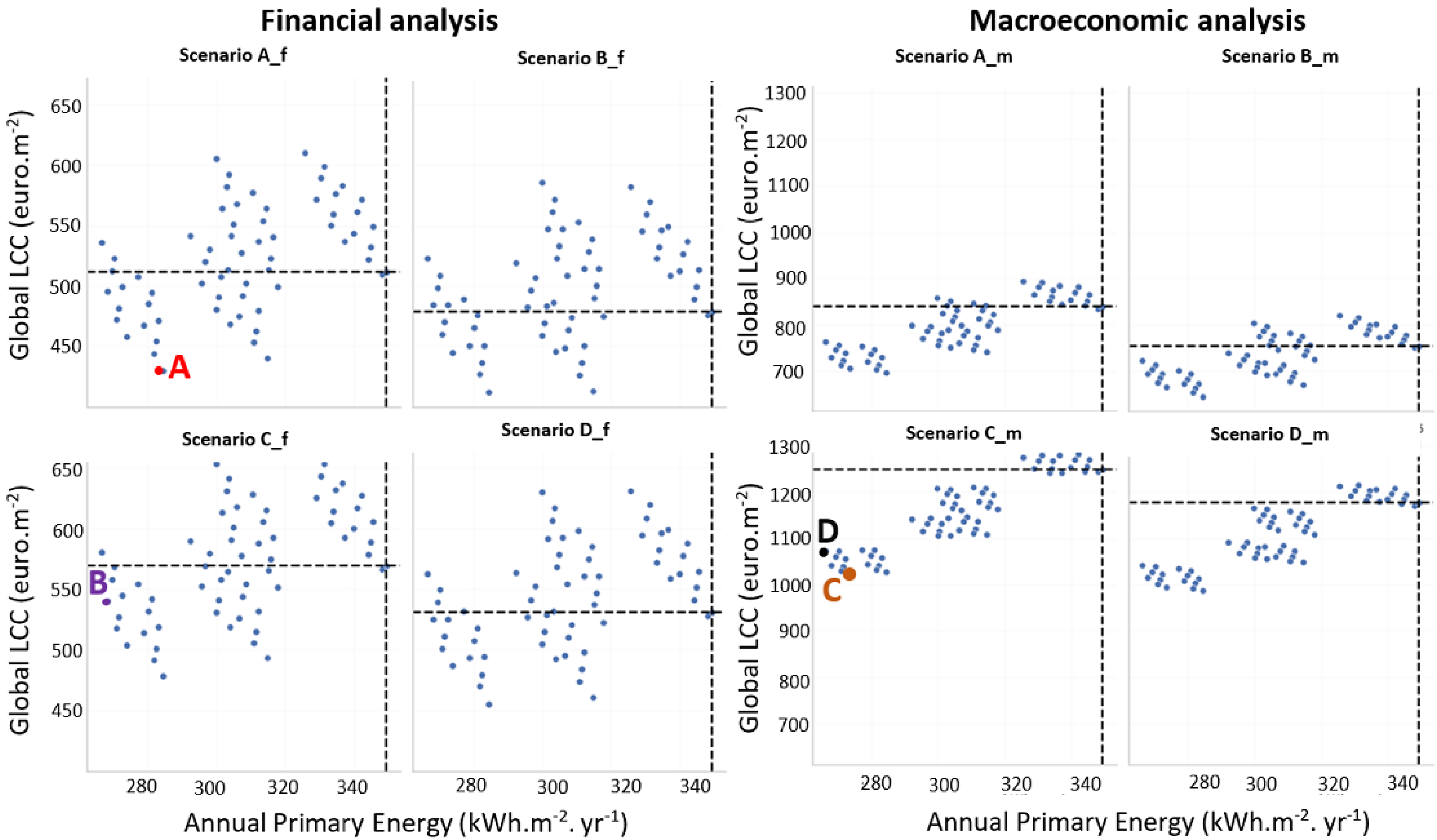


Figure 7. The four NZEB EP benchmarks derived for the case study for the year 2018-10. Point A, Point B, Point C, and Point D coincide with the COM, giving the low, high, medium, and highest NZEB EP benchmarks, respectively, as described in Table 5.

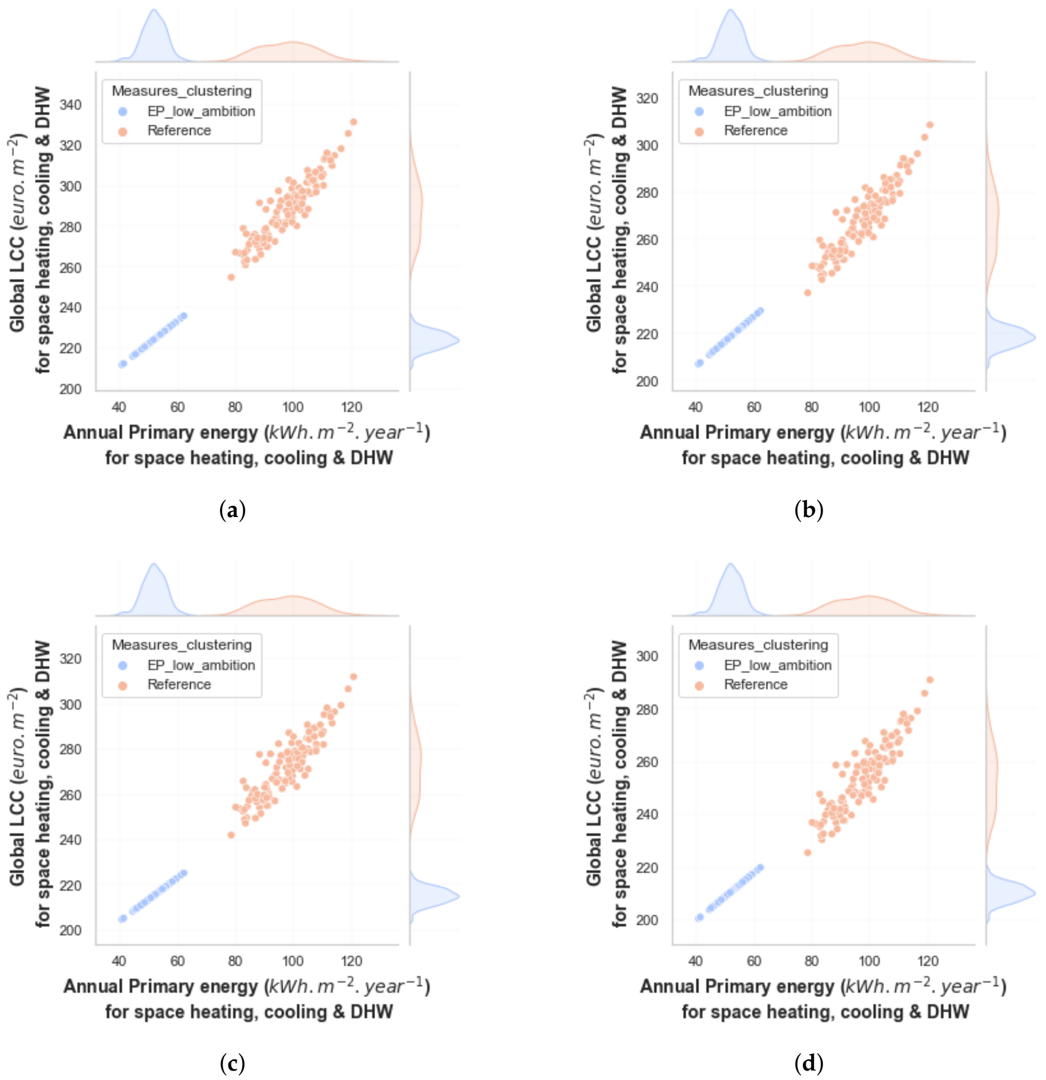


Figure 8. Joint plots combining scatter plots for with probability distributions to analyze operational EP and financial global LCC uncertainty of the COM corresponding to the low ambition NZEB EP benchmark versus the 'reference' scenario. (**a**) Scenario A_f: PD 1, DR 1 (3.2%); (**b**) Scenario B_f: PD 1, DR 2 (4%); (**c**) Scenario C_f: PD 2, DR 1 (3.2%); (**d**) Scenario D_f: PD 2, DR 2 (4%).

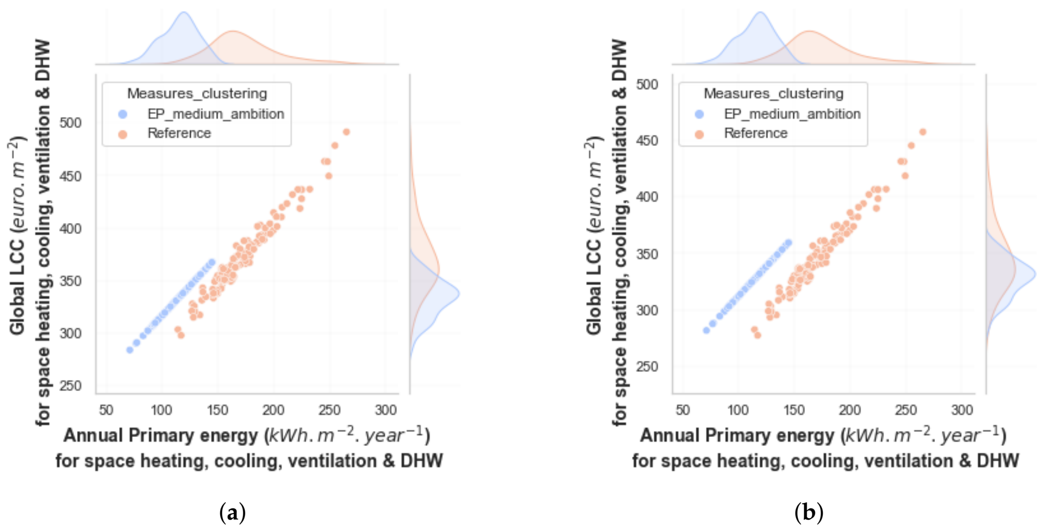
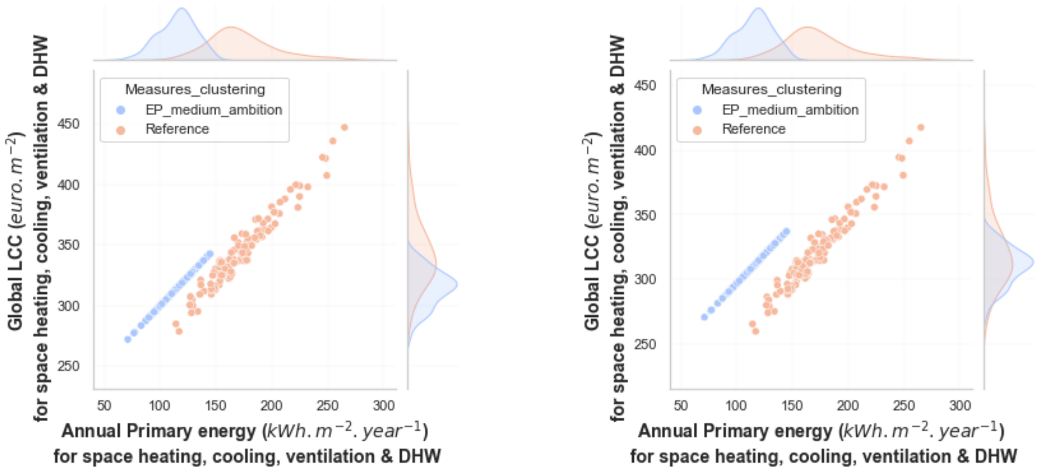
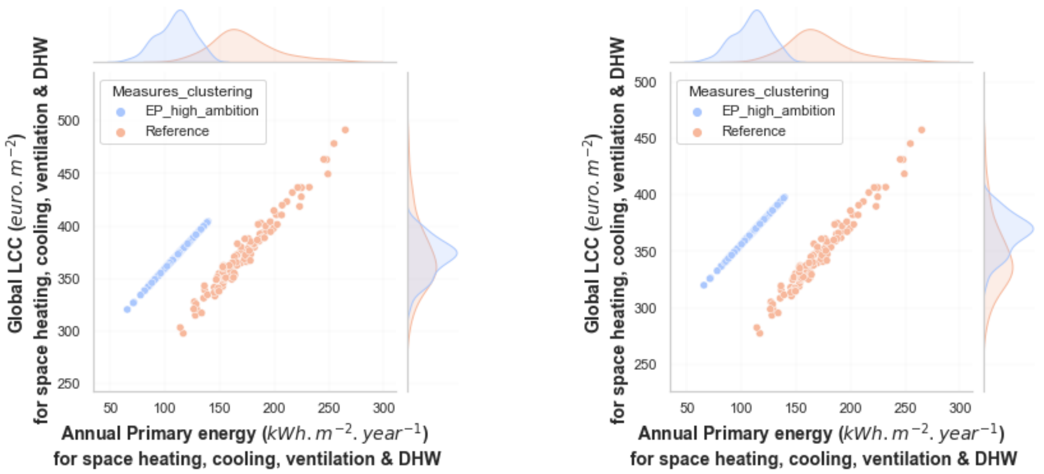


Figure 9. *Cont*.

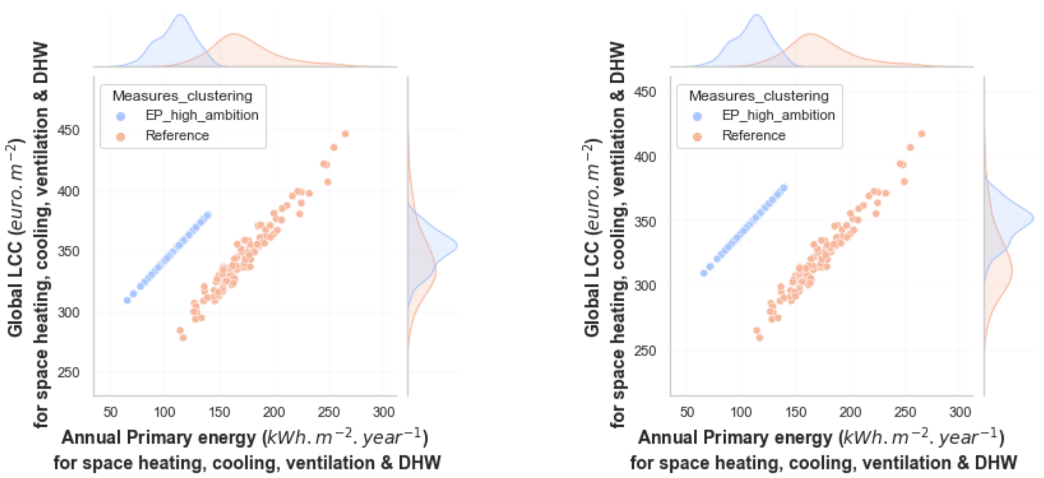


(**c**) (**d**)

Figure 9. Joint plots combining scatter plots for with probability distributions to analyze operational EP and financial global LCC uncertainty of the COM corresponding to the medium ambition NZEB EP benchmark versus the 'reference' scenario. (**a**) Scenario A_f: PD 1, DR 1 (3.2%); (**b**) Scenario B_f: PD 1, DR 2 (4%); (**c**) Scenario C_f: PD 2, DR 1 (3.2%); (**d**) Scenario D_f: PD 2, DR 2 (4%).



(**a**) (**b**)



(**c**) (**d**)

Figure 10. Joint plots combining scatter plots for with probability distributions to analyze operational EP and financial global LCC uncertainty of the COM corresponding to the high ambition NZEB EP

benchmark versus the 'reference' scenario. (**a**) Scenario A_f: PD 1, DR 1 (3.2%); (**b**) Scenario B_f: PD 1, DR 2 (4%); (**c**) Scenario C_f: PD 2, DR 1 (3.2%); (**d**) Scenario D_f: PD 2, DR 2 (4%).

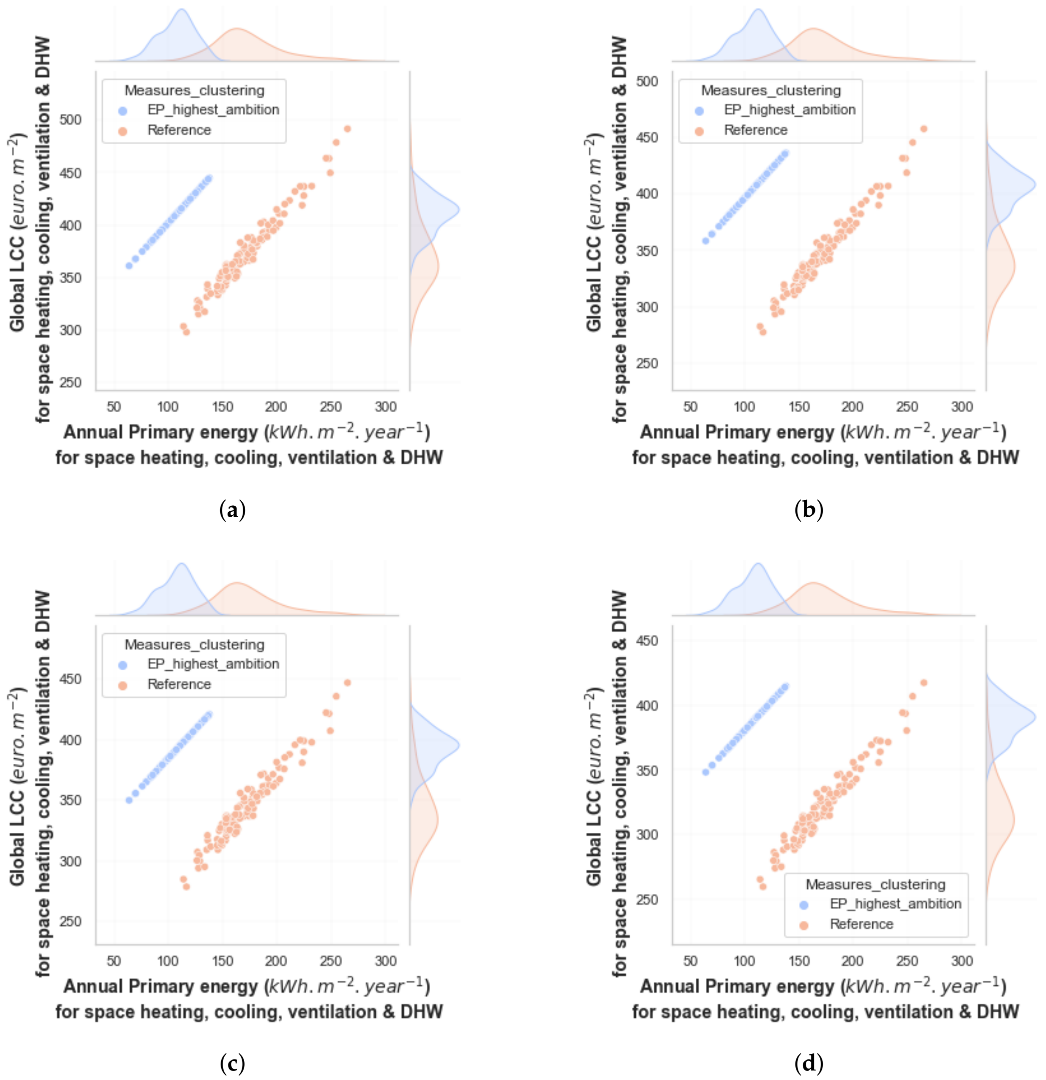


Figure 11. Joint plots combining scatter plots with probability distributions to analyze operational EP and financial global LCC uncertainty of the COM corresponding to the highest ambition NZEB EP benchmark versus the 'reference' scenario. (**a**) Scenario A_f: PD 1, DR 1 (3.2%); (**b**) Scenario B_f: PD 1, DR 2 (4%); (**c**) Scenario C_f: PD 2, DR 1 (3.2%); (**d**) Scenario D_f: PD 2, DR 2 (4%).

Table 6 compares the results of the deterministic risk (derived from using cost-optimal plots in Section 3.1.3 using the mean value of the posterior calibrated distributions) and the robust global LCC financial risks for each NZEB EP ambition level for all years 2017 to 2019. The financial risk results are also presented visually for the year 2018_10 in Figure 12 for each financial perspective scenario. It should be noted that negative financial global LCC risk values shown in Table 6 and Figure 12 translate into financial feasibility (Net Present Value (NPV > 0)) that will add value to the private investor. Furthermore, from Table 6 and Figure 12, one can conclude that the financial global LCC risk is not very sensitive to the financial perspective scenarios considered for this RB case study.

Table 6. Comparison of the resulting deterministic versus robust global LCC financial risk calculation for each NZEB EP ambition level and financial perspective scenario for the years 2017 to 2019.

		2017 Global LCC Financial Risk (euro.m^{-2})		2018 Global LCC Financial Risk (euro.m^{-2})		2018_10 Global LCC Financial Risk (euro.m^{-2})		2019 Global LCC Financial Risk (euro.m^{-2})	
NZEB EP Ambition Benchmark Level	**Financial Perspective Scenario**	**Deterministic**	**Robust (Equation)**	**Deterministic**	**Robust (Equation (3))**	**Deterministic**	**Robust (Equation (3))**	**Deterministic**	**Robust (Equation (3))**
Low	A_f	−87	−19	−94	−35	−89	−30	−91	−33
	B_f	−78	−7	−83	−22	−79	−18	−80	−21
	C_f	−71	−16	−78	−31	−73	−26	−75	−29
	D_f	−62	−5	−68	−19	−64	−14	−65	−17
Medium	A_f	−61	80	−68	67	−63	69	−65	66
	B_f	−50	92	−56	80	−51	82	−52	79
	C_f	−40	74	−46	62	−41	64	−43	62
	D_f	−29	86	−35	75	−30	77	−32	75
High	A_f	−27	115	−33	101	−27	105	−30	98
	B_f	−14	129	−19	116	−14	120	−16	113
	C_f	−4	110	−9	97	−3	101	−7	95
	D_f	8	124	3	112	8	116	6	111
Highest	A_f	14	155	8	141	14	145	10	138
	B_f	27	167	21	154	27	158	24	151
	C_f	35	150	29	138	35	141	31	136
	D_f	47	162	42	151	47	154	44	149

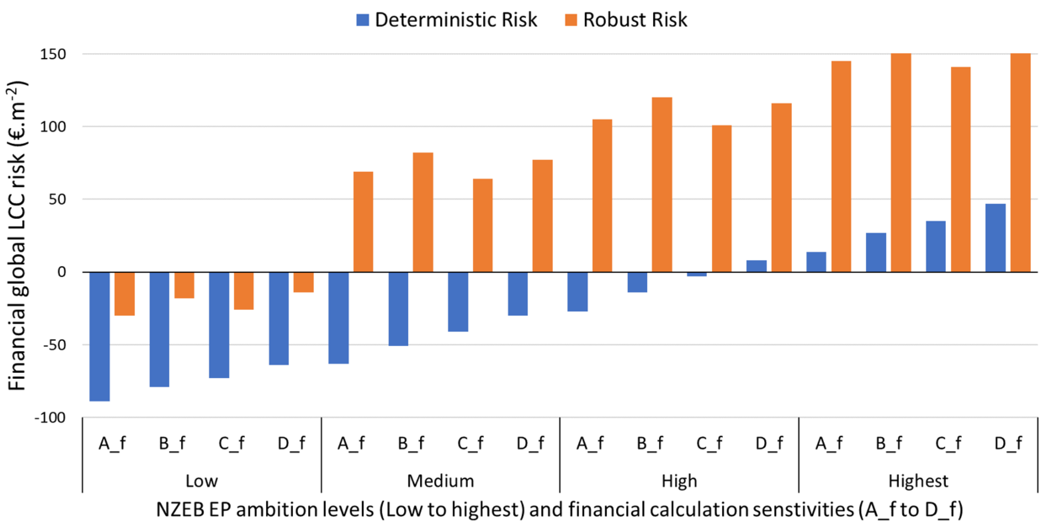


Figure 12. Comparison of the resulting deterministic versus robust global LCC financial risk calculation for each NZEB EP ambition level and financial perspective scenario for the year 2018_10.

Both the deterministic and robust risk values are negative for all the financial perspective scenarios for the low NZEB EP ambition level. Therefore, upgrading the building to the low NZEB EP ambition level is robust to financial risk and is demonstrated to be feasible to the private investor without the need for fiscal support. The risk analysis joint plots in Figure 8 reflect these results and show that the global LCC distribution plots for the 'reference' and low ambition scenario do not intersect for all considered financial perspective scenarios. It should be noted, however, that the deterministic risk values provide financial feasibility outcomes that are more optimistic than the robust risk values for the low ambition level for all years and financial perspective scenarios, as depicted in Table 6.

When performing energy retrofitting to the medium ambition level, the results of deterministic financial risk also show financial feasibility regardless of the financial perspective scenario. However, in contrast to the low ambition level, the robust financial risk values and the corresponding intersecting distributions in the joint plot (refer to Figure 9) show that upgrading to the medium ambition level does not provide a robust risk-free implementation for the private investor. A similar trend in the deterministic and probabilistic risk analysis outcomes is also observed for the high ambition level. However, for the high ambition level, the financial risk values are higher, and the financial feasibility is low to negligible even for the more optimistic deterministic analysis.

Furthermore, as expected, the highest ambition level has the least financial feasibility outcome because, regardless of the risk analysis performed, deterministic or probabilistic, implementing ECMs to achieve this NZEB EP benchmark is not financially feasible for the private investor and is only feasible from a macroeconomic perspective when considering the cost of operational carbon emissions. Therefore, while the current EPBD cost-optimal regulations [1,2] give the option to establish benchmarks from either the financial or macroeconomic perspective, the financial feasibility results of this study indicate that the establishment of benchmarks derived from the macroeconomic calculations should be considered with caution, as upgrading to such benchmarks can pose a high financial risk to the private investor, which is only fully exposed when calculating the robust financial risk from the probabilistic risk analysis.

The financial risk results for an RB representing a cluster of buildings in UBEM can be interpreted as follows. As shown from the deterministic risk results for the medium and, to a lesser extent, the high ambition levels, if one considers a cluster where each building observation is characterized only by the mean parameter values for the envelope and equipment in the analysis, the risk results could be overoptimistic and misleading for a random building observation within the building stock cluster under study, given that the robust financial risk defined by Equation (3) is not considered.

4. Comparison between the Current Deterministic EPBD Cost-Optimal Approach and the Innovative Approach for the Hotel Case Study

In the context of the hotel RB case study, this section will utilize a 'deterministic' non-calibrated RB to execute the current deterministic EPBD cost-optimal approach. The objective is to compare the NZEB EP benchmarks and financial risk results obtained in the previous section, which employed the innovative cost-optimal approach for the year 2018_10, with those derived from the current and 'deterministic' EPBD cost-optimal approach. For this purpose, the SBEM-MT software [27] is used as a building energy modeling tool to perform the 'deterministic' cost-optimal approach for this study, as it is the asset rating NCM for Malta. SBEM-MT was also used to carry out the 2018 cost-optimal studies for non-residential buildings [49]. Unlike EnergyPlus, a fully dynamic simulation tool, SBEM-MT, uses the ISO 13790 [59] monthly quasi-steady state calculation method, as explained by the author in Gatt [60], to evaluate annual energy use for space heating and cooling.

The geometry and envelope construction of the hotel EnergyPlus model was first replicated in the SBEM-MT software to enable the above-mentioned comparison between the two approaches. Given that NCM for Malta is based on an asset rating approach, SBEM-MT operates under standard conditions, and all occupancy and equipment schedules, including comfort and IAQ parameter set points, are fixed and could not be changed. Furthermore, the software does not allow the modeler to customize the equipment plug-load parameters.

To provide a comprehensive comparative analysis of the results achieved from the proposed EPBD cost-optimal approach with the current approach, an SA on the impact of the SBEM-MT input parameter values on the NZEB EP benchmarking outcome was carried out by defining two RB SBEM-MT models, with the HVAC and DHW equipment parameters characterized as follows:

1. **Asset SBEM-MT (mean_calib_par) model**: This model is characterized by the VRF space cooling and heating COP, the DHW boiler efficiency, and the fan ventilation pressure rise having the mean value of the calibration parameters posterior distributions summarized in Appendices A and B. This SBEM-MT model allows direct

comparison with the calibrated RB EnergyPlus model used to derive the NZEB EP benchmarks in Section 3.1.

2. **Asset SBEM-MT (datasheet_par) model**: This model is characterized as the above 'Asset SBEM-MT (mean_calib_par) model' but with a space heating and cooling COP of 3.8 and 4.42, respectively. These reflect the seasonal COP values found in the manufacturer's data sheet for this case study and, in the absence of a calibration exercise with metered EP data, can be deemed to be the most appropriate values to characterize the energy models.

For both of these models, the NZEB EP benchmarking process, as detailed in Section 2.1, was performed using SBEM-mt instead of EnergyPlus. The same ECMs and EN 15459 [28] global LCC parameters were applied, as defined in Sections 3.1.1 and 3.1.2, respectively, for the RB case study. The only difference in the input parameters of the benchmarking process was specifically for the 'Asset SBEM-MT (datasheet_par)' model. In this model, active measure MA1 described in Table 2 was characterized by the initial COP parameter values of 3.8 and 4.42 for space heating and cooling, respectively, as discussed above, and by the final parameters having COP values of 4.2 and 6.8 for space heating and cooling, respectively. These final parameter values reflect the high efficiency seasonal values for space heating and cooling used in the cost-optimal studies for Malta [49].

As shown in Table 7, the primary energy consumption of the calibrated model for the reference scenario matches the annual operational primary energy consumption with a discrepancy or energy performance gap of only 0.3%, while the SBEM models overestimate the energy consumption with an EP gap greater than 35%, specifically 37.5% and 49.3% for the 'Asset SBEM-MT (datasheet_par)' and 'Asset SBEM-MT (mean_calib_par)' models, respectively.

Table 7. Comparison of the primary energy consumption for the 'reference scenario' and the resulting % EP gap for the RB energy models under study.

RB Model	Reference Scenario Primary Energy Consumption (kWh.m^2.yr^{-1})	% Energy Performance Gap
Calibrated EnergyPlus model	348	−0.29
Asset SBEM-MT (mean_calib_par)	521	49.28
Asset SBEM-MT (datasheet_par)	480	37.54

This EP gap resulting from the Asset Rating outcome of the EPC software SBEM-mt v4.2c is consistent with the local and foreign studies reviewed in various studies, such as in [6–10,12–16,61]. Thus, a detailed investigation of why the EP gap occurs for Malta, specifically concerning the SBEM-MT software, is beyond the scope of this paper, and this analysis is detailed in Vassallo [16]. However, similar to the result of this case study, Vassallo [16] also reported large EP gaps of up to 60%. Furthermore, an evaluation of the accuracy of the resulting energy end-uses of SBEM-MT compared to EnergyPlus for individual buildings has already been carried out by Bartolo [62] and Mallia [63] for non-residential buildings and is also not within the scope of this paper. However, the results of these two studies indicate that the SBEM-MT software is prone to overestimate the annual energy consumption for space heating and cooling compared to EnergyPlus.

To allow a better evaluation of the EP benchmarking results, the analysis required for the case study is simply a comparison of the resulting annual site energy end-use consumption for the reference scenario. The results of this analysis are shown in Figure 13 for the three RB models. From Figure 13, it can be seen that the largest discrepancy is for DHW, which is more than 400% higher for SBEM-mt models. The reason for this is that SBEM-mt mostly follows the UK NCM schedules that consider a 100% hotel occupancy for all months and a 60% higher DHW consumption per guest night compared to the calibrated EnergyPlus model. Furthermore, SBEM-mt clearly underestimates the auxiliary energy required to drive the mechanical ventilation fans compared to the calibrated model and does not account for the LPG consumption for the cooking equipment. In addition, the energy consumption of the artificial lighting end-use is higher for SBEM-MT models, despite not accounting for exterior lighting.

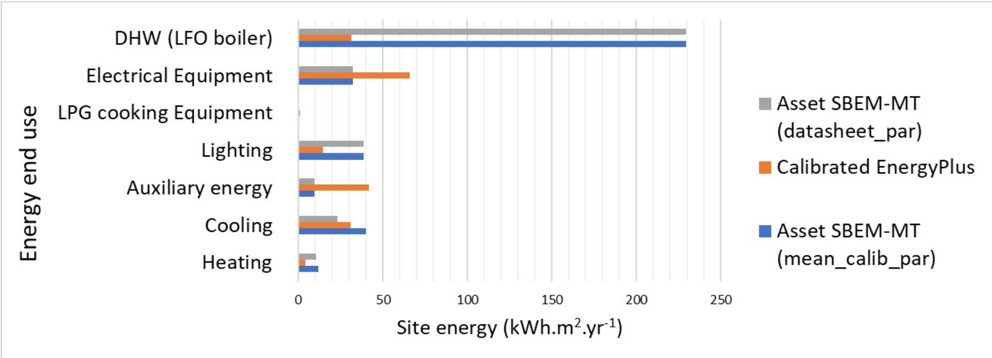


Figure 13. 'Reference scenario' site energy end-use consumption breakdown comparison between the RB energy models under study.

On the other hand, the electrical equipment consumption is higher for the calibrated EnergyPlus model since the Reverse Osmosis water treatment system was included and modeled as an electrical plug load and the food preparation areas were characterized with a higher calibrated plug load power density than the UK NCM values reflecting the findings of local hotel energy audits.

These differences in energy end-uses between the SBEM-MT and the EnergyPlus calibrated model result in a significant discrepancy in the EP benchmarks and the corresponding ECMs for each NZEB EP ambition level, as shown in Table 8 and Figure 14.

Table 8. Comparison of the resulting NZEB EP benchmarks and corresponding COMs for the RB energy models under study.

RB Energy Model	NZEB EP Benchmark Level	Primary EP Benchmark ($kWh.m^2.yr^{-1}$)	% EP Improvement from Reference Scenario	Passive ECMs			Active ECMs		
				MP1	MP2	MP3	MA1	MA2	MA3
Calibrated EnergyPlus Model	Reference	348							
	Low	284	18.4				x	x	
	Medium	273	21.6				x	x	x
	High	268	23	x	x		x	x	x
	Highest	266	23.6	x	x	x	x	x	x
Asset SBEM-MT (mean_calib_par)	Reference	521							
	Low	228	56.3				x	x	
	Medium	215	58.7	x			x	x	
	High	204	60.9	x	x	x	x	x	x
	Highest	204	60.9	x	x	x	x	x	x
Asset SBEM-MT (datasheet_par)	Reference	480							
	Low	237	50.6					x	
	Medium	210	56.3	x			x	x	
	High	201	58.1	x	x	x	x	x	x
	Highest	201	58.1	x	x	x	x	x	x

Given the above difference in the energy consumption end-uses, most notably the overestimation for the DHW energy end-use consumption predicted by the SBEM-MT models, both SBEM-MT models provide a much more optimistic scenario in the potential EP improvements that are achievable for each NZEB EP benchmark. More specifically, the maximum potential in EP improvements is 60.9% for the SBEM-MT models versus 23.6% for the calibrated EnergyPlus model. Furthermore, the resulting COMs corresponding to each ambition NZEB EP benchmark are different between the EnergyPlus and SBEM-MT models. For the SBEM-MT models, ECM MA3 only appears first at the high EP ambition level instead of the medium EP ambition level as for the calibrated EnergyPlus model, mainly due to the underestimated annual auxiliary energy consumption in SBEM-MT. Similarly, passive ECM MP3 appears both at the high and highest EP ambition levels versus only at the highest EP ambition level for the calibrated EnergyPlus model.

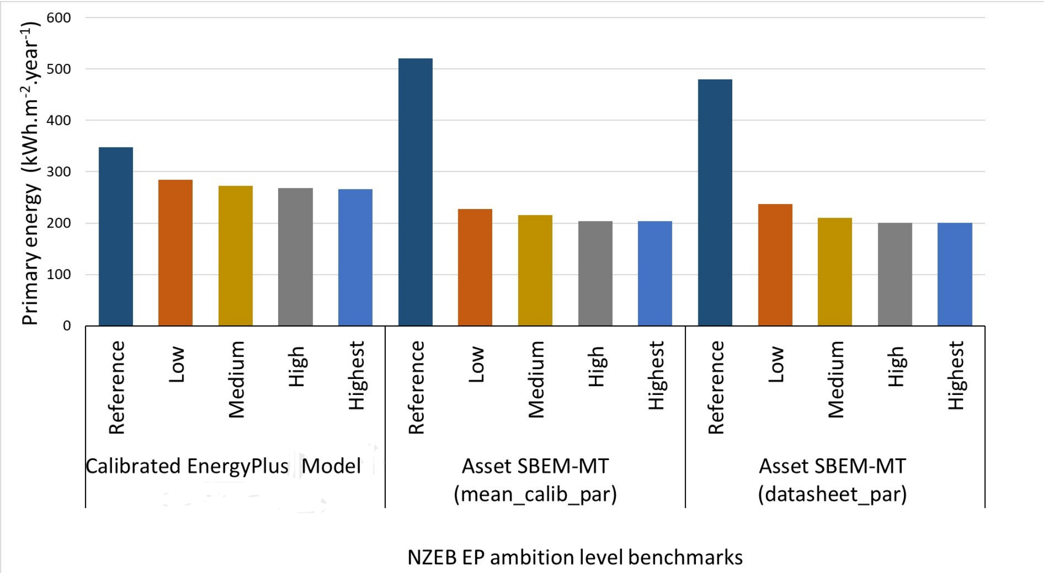


Figure 14. Comparison of NZEB EP benchmarks obtained for the different RB energy models under study.

It should be noted that although the resulting NZEB EP benchmarks defined in kWh.m^{-2}.yr^{-1} are fairly consistent between the two SBEM-MT models, some discrepancies can be observed from Table 8 in the resulting COMs corresponding to each ambition NZEB EP. More specifically, active ECM MA1 does not appear for the 'Asset SBEM-MT (datasheet_par)' model at the lower ambition benchmark level as opposed to the other models, because, as shown in Figure 13, its lower annual energy end-use consumption for space cooling results in a reduced potential for energy savings when implementing ECM MA1.

The deterministic global LCC financial risk results were also calculated, as discussed in Section 2.1, for the SBEM-MT models directly from the resulting cost-optimal plots. These results are compared directly to the deterministic and robust global LCC financial risk result obtained for the calibrated EnergyPlus RB model discussed in the previous section, as shown in Figure 15. It is evident that both SBEM-MT models portray a very optimistic scenario for financial risk in contrast to the calibrated EnergyPlus model. From the analysis, it is shown that for the SBEM-MT models, even upgrading the RB to the highest ambition EP level is still financially feasible to the private investor, irrespective of the financial sensitivity scenario under consideration.

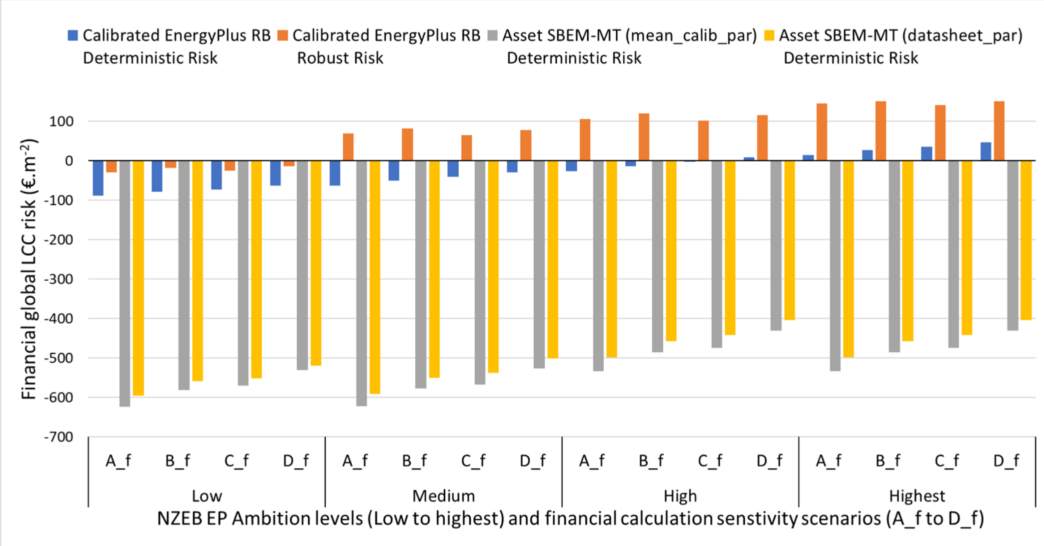


Figure 15. Comparison of the resulting financial global LCC risk for the different RB energy models under study for each NZEB EP ambition level and financial perspective scenario. For the calibrated RB EnergyPlus model, both robust and deterministic risk are evaluated, while only deterministic risk is considered for the Asset SBEM-MT models.

5. Discussion

The case study results above indicate that a deterministic risk assessment is prone to provide an over-optimistic financial feasibility outcome. Thus, performing only a deterministic risk assessment without a probabilistic risk analysis can make mandating minimum EP requirements to higher ambition levels, such as the medium or high versus low NZEB EP benchmark for the RB case study, a natural choice for the entire building stock to maximize reductions in GHG emissions. However, as shown from the probabilistic risk analysis, mandating to these higher ambition benchmarks without providing financial support can negatively impact individual buildings with unsustainable EP and unrealistic benchmarks that are counterproductive in the long term [64]. This outcome may decrease investors' faith in the policy-making procedure as well as the overall desired outcomes of the energy renovation of the building stock under consideration. Moreover, this would go against the general spirit of the EPBD that energy efficiency measures need to be financially feasible.

The case study results also demonstrate the economic law of diminishing marginal utility for the energy renovation of the building stock, as highlighted by the EC [65]. The low level of EP ambition in the RB case study addresses the low-hanging fruit, which is shown in Table 5 to provide more than 70% of the EP improvements achievable by the highest NZEB EP benchmark and is economically feasible for all financial risk scenarios. Making such results transparent to investors and ESCOs for different building stocks provides them with a better assurance of the financial and energy savings benefits of performing energy renovation, thus addressing the uncertainty barrier and triggering energy renovation. Although this does not undermine the importance of focusing on deep energy renovation, as highlighted in the EU energy renovation wave [66], renovation as a minimum to ambition levels that address low-hanging fruit is critical for MS to meet the carbon neutrality goals for 2050, as this renovation provides the highest potential for EP improvements in building stock.

For mandating higher EP ambition levels to trigger deeper energy renovation, a probabilistic risk analysis also provides the appropriate framework to objectively quantify the necessary financial support measures to trigger energy renovation. This quantification is critical, as the lack of appropriate financial incentives for commercial buildings was found by the EC to be a relevant barrier to energy renovation [66]. More specifically, within this framework, a customized financial incentive value can be attributed to a building based on the recommendation of a certified EPC assessor or an approved energy auditor and with a maximum incentive threshold equal to the robust risk value for a given ambition level. The total financial incentive can still be budgeted by MS using the deterministic risk calculated for each level of ambition and identifying the number of buildings to be targeted. This financial support can then be coupled with a time-bound tightening approach to higher EP ambition levels, as discussed in Section 2.1, with the financial support progressively reduced within this long-term framework. Such long-term EP targets and a progressive reduction in financial incentives trigger an improvement in the learning rate [67] to achieve a self-sustainable framework for investors that continuously improves the EP of building stocks for a sustainable renovation path with minimal financial incentives.

In addition, the probabilistic risk analysis allows policy makers to quantify the impact of wide calibration parameter posterior distributions in the decision-making process of defining NZEB EP benchmarks and when quantifying financial incentive requirements. The narrowing of the posterior calibrated parameter distributions results in less uncertainty in the probabilistic risk analysis step that consequently allows the definition of NZEB EP more targeted benchmarks and financial incentives for effective and more ambitious policy making. The need for narrower posterior calibration parameter distributions will automatically trigger policy makers to gather more data and define more informative priors in the Bayesian calibration process. Alternatively, a more refined RB clustering approach can be established to better handle the diversity of heterogeneous building stocks. The Bayesian calibration approach coupled with a probabilistic risk analysis framework in the proposed EPBD cost-optimal method, therefore, has the advantage of allowing for a continuous and progressive learning process in policy making.

Clearly, the over-optimistic results for financial feasibility of SBEM-MT are not credible. For example, one can observe from Figure 15 that both SBEM-MT models show that upgrading to the highest EP ambition level is up to four times more financially feasible than when upgrading the calibrated Energy Plus RB model to the low ambition level using the more optimistic deterministic financial risk scenario. Such a discrepancy cannot be underestimated, and therefore, it is not wise to commit to maximum renovation measures based on the SBEM-MT results, when the calibrated Energy Plus RB model results demonstrate a significant financial risk.

Therefore, using uncalibrated RB models with ECMs tends to produce optimistic EP and carbon emission savings, as well as unrealistic financial feasibility, which in the long run could result in loss of investment and reduced confidence in the energy models. Consequently, a change in direction will need to be implemented by using calibrated models that take into consideration not only calibration with actual energy consumption for the reference building for each category under consideration but also the range of probabilistic risk encountered in energy savings and costs.

6. Conclusions

In conclusion, this paper introduced a comprehensive framework for the development, application, and successful validation of the NZEB EP benchmarking and the probabilistic risk analysis stages of the proposed novel EPBD cost-optimal method. The proposed cost-optimal method replaces 'non-calibrated deterministic RBs' with 'probabilistic Bayesian calibrated RBs', offering a superior approach to handling parameter uncertainties and building stock diversity.

A critical gap in the current EPBD cost-optimal method is addressed by presenting an objective approach to defining NZEB EP benchmarks. Categorized into four ordinal levels of EP ambition, this approach provides MS with a harmonized and easily implementable approach to NZEB bench-marking, fostering a step-change pathway towards the much-needed decarbonization of buildings.

For the probabilistic risk analysis, a robust approach has been developed and validated using posterior calibrated parameter distributions for a case study RB. The outcomes demonstrate a more realistic quantification of financial risk for each identified NZEB EP ambition level benchmark, thus enabling private investors and policy makers to make informed decisions on the pathway towards decarbonization.

The developed framework significantly advances the current deterministic financial feasibility analysis of the EPBD cost-optimal method. It adds transparency to potential financial risks associated with the implementation of ECMs for different energy efficiency ambition levels, progressively leading to full decarbonization of buildings.

The study also credibly underscores the need for calibrating NCM software(s) with operational EP data and using probabilistic approaches to integrate risks in the decision-making process for EPBD cost-optimal analysis and subsequent policy making, including financial support decisions. Only through this approach can the prevailing reported EP gap be minimized and financial risks associated with acting on misleading optimistic EP results be avoided.

All in all, the proposed approach contributes to fulfilling some of the most pressing requirements of the EPBD, including enabling MS to establish stronger 'long-term' renovation strategies. This is possible through the establishment of more realistic EP benchmarks by calibrating RBs with individual metered building stock data. Furthermore, defining multiple NZEB benchmarks provides the potential of a time-bounding approach to higher ambition levels, allowing for the objective definition of deep renovation. The risk and uncertainty analysis also enhances transparency in the cost-optimal calculations, addressing the financial risk barrier for the renovation of the building stock. Last but not least, when the proposed approach is coupled with the latest EPB standards established under mandate M/480 [68], the reduction in EP gap and a more objective NZEB benchmarking approach will contribute to achieving the EPBD goal of defining more cross-national comparable EP benchmarks. Such EP benchmarks and policies can also be more targeted through a continuous building stock learning process for policy makers, thanks to Bayesian calibration.

Future research should focus on enhancing the calibration process by incorporating higher resolution energy consumption data, potentially including submetering data, to assess its impact on NZEB EP benchmarks and probabilistic financial risk analysis. It should also explore optimal approaches to handle uncertainties and the diversity of global LCC financial parameters, such as the capital costs of ECMs, beyond the current EPBD requirements of performing only SA on the PD and DR. Additionally, the potential application of multi-objective genetic algorithms in the proposed cost-optimal analysis should be investigated to expedite convergence to the NZEB EP ambition levels, as opposed to conducting a full parameterization exercise simulating all potential COMs.

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Abbreviations

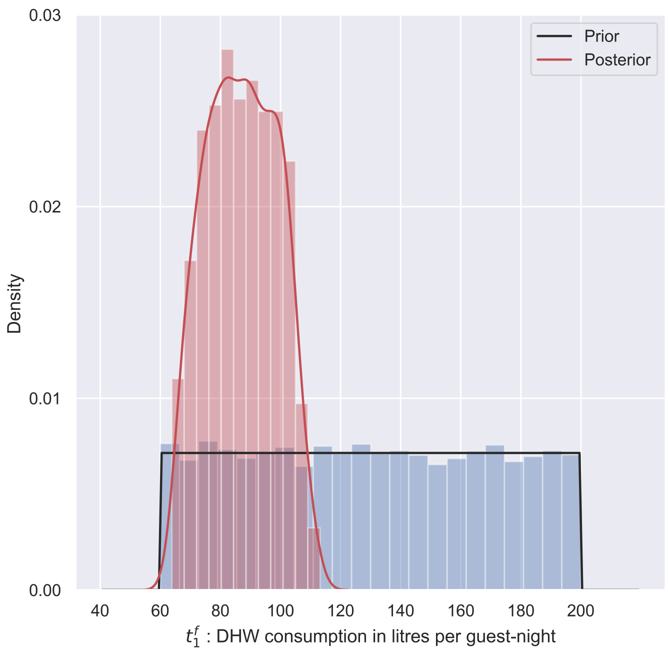
The following abbreviations are used in this manuscript:

ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
ACH	Air Changes per Hour
BEM	Building Energy Modeling
BEMs	Building Energy Models
COM	A package (combination) of energy efficiency measures
COP	Coefficient of Performance
COMs	Sets of packages (combinations) of energy efficiency measures
CVRMSE	Coefficient of the Variation of the Root Mean Square Error
DHW	Domestic Hot Water
DOAS	Dedicated Outdoor Air System
DRs	Discount Rates
DR	Discount Rate
EC	European Commission
ECMs	Energy Conservation Measures
ECM	Energy Conservation Measure
EP	Energy Performance
EPB	Energy Performance of Buildings
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
EPCs	Energy Performance Certificates
ETS	Emissions Trading System
EU	European Union
EUI	Energy Use Intensity
GDP	Gross Domestic Product
GHG	Greenhouse Gas
HDI	Highest Density Interval
HR	Heat Recovery
HVAC	Heating, Ventilation, and Air Conditioning
IAQ	Indoor Air Quality
ISO	International Organization for Standardization
LCC	Life-cycle Costs
LFO	Liquid Fuel Oil
LHS	Latin Hypercube Sampling
LPG	Liquefied petroleum gas
MCMC	Markov chain Monte Carlo
MCSE	Monte Carlo Standard Error
M-H	Metropolis–Hastings
MS	EU Member States
MV	Mechanically Ventilated
NCM	National Calculation Methodology
NMBE	Normalized Mean Bias Error
NPV	Net Present Value
NZEB	Nearly Zero Energy Building
PD	Price Development
POTEnCIA	Policy Oriented Tool for Energy and Climate Change Impact Assessment
RAR	Remove and Replace
RO	Reverse Osmosis
RB	Reference Building
RBs	Reference Buildings
SBEM-MT	Simplified Building Energy Model for Malta
SFP	Specific Fan Power
SHGC	Solar Heat Gain Coefficient
UBEM	Urban Building Energy Modeling
UBEMs	Urban Building Energy Models
UK	United Kingdom

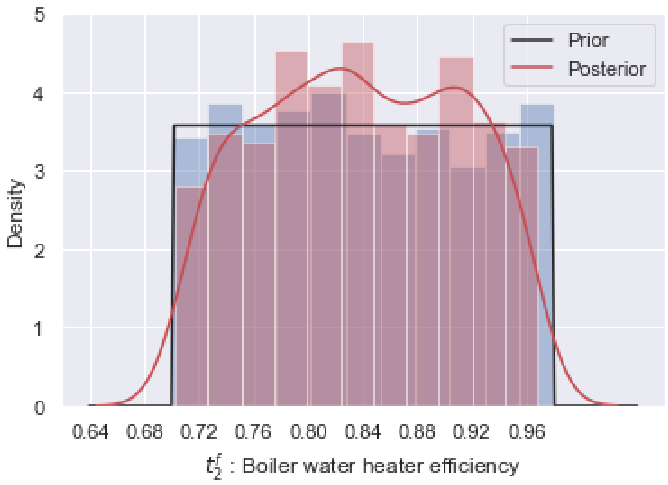
VAT	Value Added Tax
VRF	Variable Refrigerant Flow

Appendix A

This Appendix replicates from [5] the prior and resulting posterior distributions of the DHW calibration parameters for the Hotel EnergyPlus RB case study.



(**a**)



(**b**)

Figure A1. The prior and resulting posterior distributions of the DHW energy model calibration parameters for (**a**) t_1^f: DHW consumption in litres per guest night and (**b**) t_2^f: Boiler water heater efficiency. The prior (blue distributions) and resulting posterior distributions (red distributions) of the DHW calibration parameters are shown in the picture.

Appendix B

This Appendix replicates from [5] the prior and resulting posterior distributions of the electricity end-uses calibration parameters for the Hotel EnergyPlus RB case study.

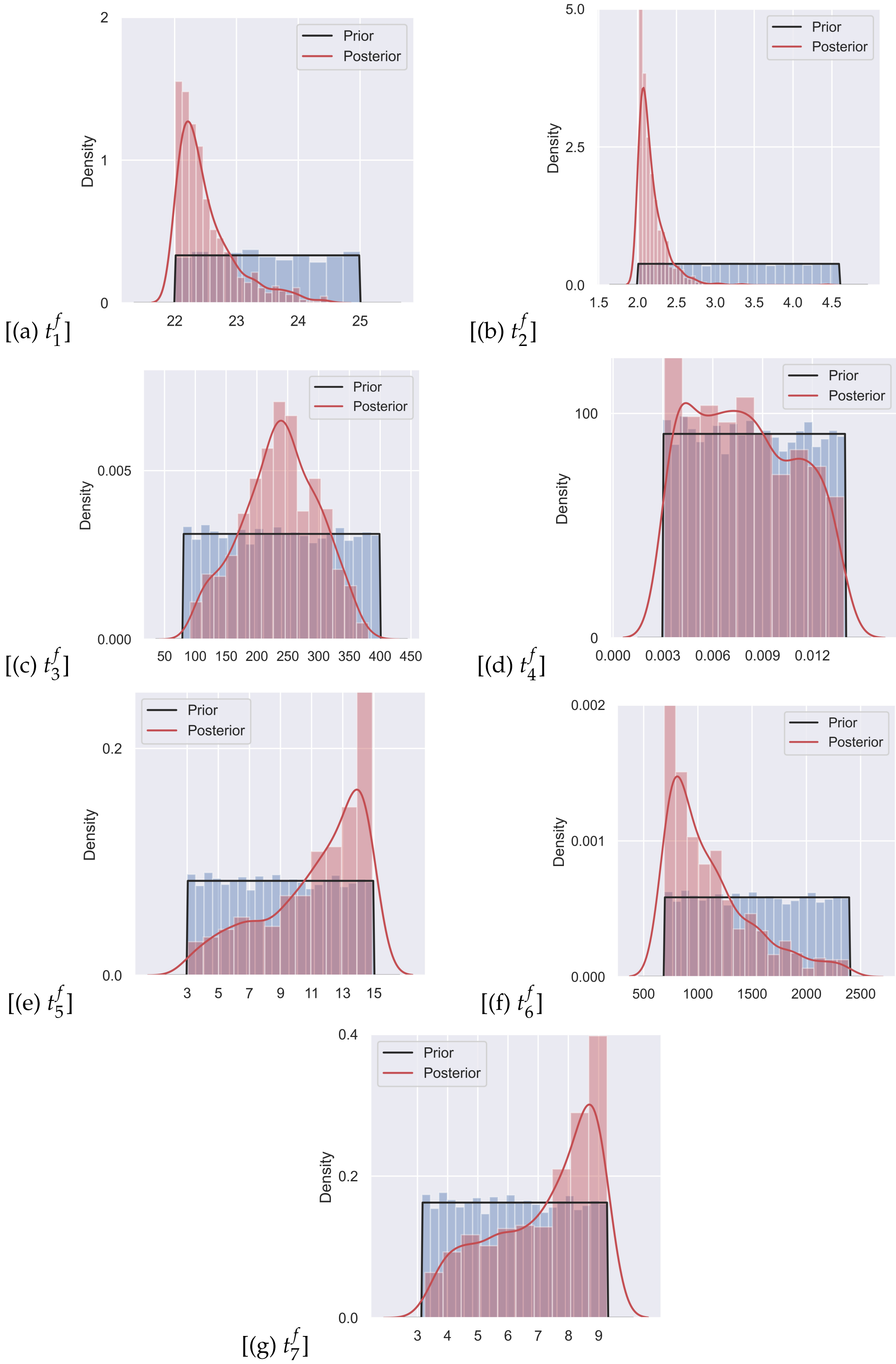


Figure A2. The prior and resulting posterior distributions of the electricity end used energy model calibration parameters for (**a**) t_1^f: Guest rooms' cooling temp set-point (deg C), (**b**) t_2^f: VRF cooling COP, (**c**) t_3^f: Kitchen equipment power density (W.m^{-2}), (**d**) t_4^f: FOH ventilation rate (m^3.s^{-1}.person^{-1}), (**e**) t_5^f: BOH Zone ACH, (**f**) t_6^f: Fan ventilation pressure rise (Pa) and (**g**) t_7^f: Guest rooms' equipment power density (W.m^{-2}). The prior (blue distributions) and resulting posterior distributions (red distributions) of the electricity end uses energy model calibration parameters are shown in the picture.

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