Optimal Design of Building Energy Systems under long-term Uncertainties

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Abstract:

The decarbonization of the building sector requires a rapid transition to electrified heating systems, with heat pumps emerging as a cornerstone technology. However, conventional design practice of building energy systems relies on static calculation methods based on normative standards, which do not explicitly account for long-term uncertainties in electricity markets, climate evolution, or temperature requirements. This approach often results in conservatively oversized and expensive energy systems. Uncertainty quantification frameworks demonstrate that design choices for specific building energy systems use cases are significantly influenced by parameter variability, highlighting the need for design approaches under multiple uncertainties. While seminal stochastic optimization frameworks exist for energy system design, a practical methodology is needed to guide building-level investment decisions across a comprehensive portfolio of technologies, translating complex risk analysis into actionable design choices. This paper presents a systematic, multi-step methodology to identify economically resilient building energy system designs under multiple long-term price uncertainties. The approach involves: (1) performing separate deterministic design optimizations for a set of distinct long-term energy price scenarios; (2) grouping the resulting optimal designs into representative design clusters using a clustering algorithm; (3) conducting a cross-scenario evaluation to assess the performance of each design cluster across all possible futures; and (4) identifying the most robust design based on its expected total annualized cost and its uncertainty. The methodology models four key energy carrier price uncertainties: housing electricity, heat pump electricity, natural gas and biogas price. Applying the methodology to a representative building in Germany, the results demonstrate that all-electric designs centered on a heat pump, photovoltaics and battery storage are the most resilient, having a 12% higher upfront investment than a benchmark design optimized for a single forecast, offers a 1% lower expected total annualized cost but, more significantly, reduce long-term economic risk by lowering cost volatility by up to 7%. The proposed methodology functions as a transparent decision-support instrument, enabling stakeholders to identify system designs that are not only cost-effective for an assumed future, but economically resilient against the uncertain one.

Keywords:

Building Energy Systems; Uncertainty Quantification; Resilient Design; Optimization.

1. Introduction

The building sector is a significant component of the global energy system, accounting for approximately 40% of total energy consumption and 36% of energy-related CO_2 equivalent emissions in Europe [1]. The European Union's Green Deal, Germany's Federal Climate Protection Act and Building Energy Act mandate a profound decarbonization of the building sector, as its decarbonization is indispensable for achieving climate targets [1,2]. A central strategy for achieving these climate targets is the modernization of the existing building stock, primarily through the substitution of fossil-fuel-based heating systems with technologies compatible with renewable energy sources, such as heat pumps (HP) and photovoltaics (PV) [3,4].

According to [5], the retrofitting the single-family (SFH) and multi-family houses (MFH) with HP-based, PV and battery storage (BAT) supported building energy systems (BES), has the potential to reduce emissions by up to 43%. While central to decarbonization, this transformation poses challenges, including the effective integration of components and the significant investments required of building owners.

The long lifespan of these systems exceeding 20 years exposes them to significant financial risk from inherently uncertain future energy prices, as historical forecasts have often proven inaccurate [6]. A design optimized for a single forecast may underperform in plausible alternative futures, jeopardizing the initial investment. For instance, a large PV and battery investment becomes unviable if grid electricity prices fall unexpectedly. Consequently, the selection and sizing of these components must be robust against future boundary conditions to ensure both economic and environmental performance over their entire lifecycle.

1.1. State-of-the-Art in Building Energy System Design

Current design practices range from normative methods (e.g. DIN EN 12831), which often lead to oversized, expensive and inefficient systems by focusing on static peak loads [7,8], to deterministic optimization models. These advanced models, typically mixed-integer linear programs (MILP), co-optimize system design and operation to minimize metrics like total annualized cost (TAC). However, their critical limitation is the reliance on a single, perfect forecast for parameters like energy prices, which produces solutions that are mathematically optimal for one assumed future but brittle against real-world uncertainty [8–12].

To address this, uncertainty-aware methods like robust optimization and stochastic programming have been developed. At the building level, seminal works have used uncertainty and sensitivity analysis to show that energy prices and demand profiles significantly alter optimal designs and economics [11,13–16]. A more widely used approach is stochastic programming, which explicitly incorporates multiple future scenarios into the optimization process. By optimizing the expected performance across these scenarios, it finds designs that are more resilient. These methods have been successfully applied to energy systems at the district and national grid levels, demonstrating that incorporating uncertainty leads to investments with lower expected life cycle costs and reduced financial risk [14]. [11] developed a comprehensive uncertainty and global sensitivity analysis framework for distributed energy systems, showing that uncertain energy carrier prices and demand profiles can significantly alter both the economic performance and the optimal technology portfolio compared to deterministic designs. In related work, they proposed a two-stage stochastic programming formulation for distributed energy system design, where investment decisions are taken in the first stage and operational decisions adapt to multiple price and demand scenarios in the second stage, reducing expected life-cycle costs and downside risk [14]. Complementary to these distributed energy system-oriented studies, [15] introduced a robust optimization extension of a MILP retrofit model for typical buildings, demonstrating that modernization schedules and technology choices can change markedly when robustness against uncertain energy prices, emission factors, and user behavior is explicitly required [16]. Recent uncertainty quantification frameworks for district and integrated energy systems use Monte-Carlo or Quasi-Monte-Carlo sampling combined with global sensitivity analysis to show that variations in energy carrier prices, demand profiles and envelope parameters can substantially change optimal designs and their life-cycle economics, underscoring the need for design approaches that explicitly address multiple uncertainties [17,18].

While these seminal works establish the value of uncertainty analysis, a gap remains between high-level stochastic modeling and practical, building-specific design guidance. Existing frameworks often do not resolve the detailed trade-offs between the comprehensive portfolio of competing technologies available for a BES. Consequently, a clear research gap exists in developing a systematic methodology that navigates multiple, long-term uncertainties to identify not just optimal, but economically resilient designs at the individual building level.

1.2. Contribution and Paper Structure

To address this gap, this paper seeks to answer the overarching research question: How can a BES be identified as economically resilient when facing multiple long-term economic uncertainties? The paper introduces a multi-step methodology that combines deterministic optimization with principles from stochastic analysis and robust decision-making. The methodology systematically explores the solution space by combining scenario-based deterministic optimization with hierarchical clustering to identify representative design clusters and cross-evaluation to assess economic performance and resilience. This approach allows for a nuanced analysis of the trade-offs between minimizing expected costs (a stochastic goal) and ensuring performance stability, for instance by minimizing cost volatility and limiting exposure to worst-case scenarios, across all scenarios (a robustness goal). It provides actionable insights that go beyond single-scenario optimization.

To guide our investigation, we address the following specific research questions:

- How can a multi-step methodology be structured to identify resilient BES configurations that maintain economic viability across a range of long-term energy price uncertainties?
- Applying this methodology to a SFH, how do the technology selection, component sizing, and TAC of an optimal BES design derived under uncertainty compare to a design optimized using a single, deterministic price forecast?

The remainder of this paper is structured as follows. Section 2 provides a detailed description of the multi-step methodology, including the mathematical formulation of the optimization problem, the clustering procedure, and the metrics for robustness evaluation. Section 3 describes the model application on a case study, defining the reference building, the available technology portfolio, and the underlying energy price scenarios. Section 4 presents the results, followed by a discussion in Section 5 and the conclusion in Section 6.

2. Methodology

This section presents the underlying residential building optimization model and the developed methodology, which is used to identify resilient BES designs. Secondly, the developed methodology is formulated as a five-step approach, which is designed to be computationally tractable, while explicitly accounting for uncertainty in long-term energy prices by breaking down a complex problem into a series of deterministic subproblems. These problems are solved by integrating the residential building optimization model. The different prices of energy carriers under uncertainty considerations are outlined in the scenario definition. By incorporating both the defined scenarios and the residential building optimization model, optimal scenario specific designs are identified. To further reduce the number of different designs, they are clustered into representative design clusters, which are afterwards evaluated across all possible scenarios for their performance.

2.1. Optimization Framework

This paper builds upon an existing framework for the design and operational optimization of residential buildings developed by [10]. The core of the framework is an optimization model, formulated as a mixed-integer linear programming (MILP) model, that determines the cost-optimal design and operation of a residential BES. The model co-optimizes investment decisions (component selection and sizing) and operational decisions (hourly energy dispatch) for a given set of boundary conditions. The objective function minimizes the total annualized cost (TAC), which is the sum of annualized capital expenditures (CAPEX) and annual operational expenditures (OPEX):

$$\min TAC = \sum_{t \in T} CAPEX_t + OPEX_t \tag{1}$$

where T is the portfolio of available technologies. The OPEX includes costs for energy procurement from the grid and revenues from selling surplus electricity. The optimization is subject to constraints ensuring that hourly energy balances are met, and all components operate within their technical limits. To maintain computational tractability, the operational optimization is performed over a set of representative days that capture seasonal and daily variations.

A portfolio of technologies for heating, electricity, and storage is available, including air-source heat pumps (ASHP), electric heater (EH), gas boilers (BOI), photovoltaics (PV), solar thermal systems (STC), batteries (BAT), thermal storage (TES) and domestic hot water tank (TES-DHW). While the original model has the capacity to optimize building envelope measures, the present study focuses exclusively on energy system selection and sizing in order to isolate the impact of techno-economic uncertainties.

2.2. Multi-step approach

The proposed methodology for identifying robust BES designs is structured as a sequential, five-step framework, as visualized in **Figure 1**. This process is designed to be computationally tractable while explicitly accounting for uncertainty in long-term energy prices. It achieves this by decomposing a complex stochastic optimization problem into a series of deterministic subproblems and subsequent analysis steps.

The methodology outlined as follows:

1. Scenario definition
2. Scenario-specific optimization
3. Design cluster identification
4. Cross-scenario evaluation
5. Robustness analysis

The core of the analysis is the optimization framework presented in Section 2.1. The corresponding stages are described in the following.

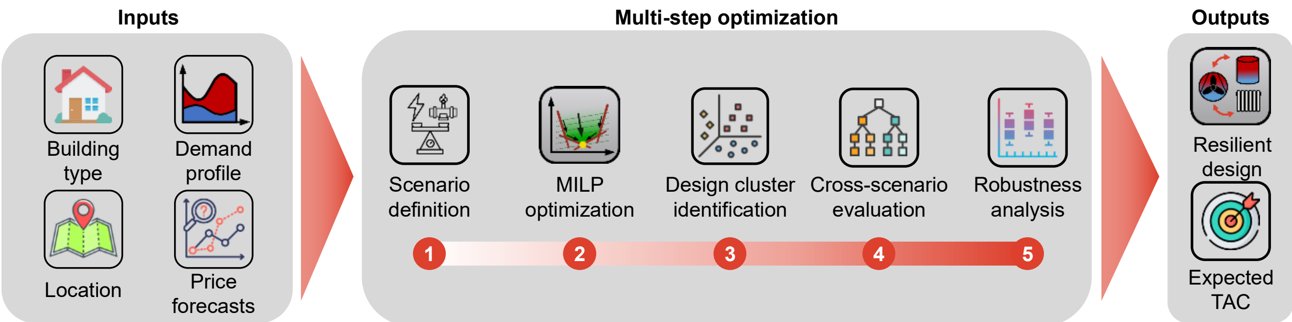

Figure 1. *The methodological framework for identifying a resilient building energy system, which processes building and uncertain price inputs through a multi-step optimization and evaluation sequence to yield a single robust design and its expected TAC.*

Scenario definition

A set of N distinct long-term energy price scenarios S is defined. Each scenario represents a unique, plausible trajectory for key energy carrier prices over the system's lifetime. This set is constructed to span a wide range of potential future economic conditions, from optimistic renewable-driven futures to scenarios with resurgent fossil fuel dominance.

Scenario-specific optimization

For each individual scenario s, a deterministic optimization is performed using the framework described in Section 2.1. This step solves the cost-optimal system design (i.e., the selection and sizing of components) and its corresponding operation, assuming perfect foresight within that single scenario. The result of this stage is a set of N potentially unique optimal designs, which collectively map out the solution space.

Design cluster identification

To manage the complexity of N unique designs, they are grouped into a smaller number of K representative clusters. Each design is represented as a numerical vector of its component sizes, and the hierarchical clustering algorithm groups these vectors into K clusters. The optimal number of clusters, K, is determined using the silhouette score, which measures cluster cohesion and separation [19]. The centroid of each resulting group is then defined as a representative design cluster, synthesizing the optimization results into a small set of distinct system configurations.

Cross-scenario evaluation

The design of each cluster is fixed (i.e., component sizes are set). Then, for each design cluster, its operational performance is simulated under every one of the N price scenarios. This is done by running a purely operational optimization to find the minimum possible OPEX for that fixed design in that specific future scenario. This process yields a cost matrix $C_{i,s}$, where each element represents the TAC of design cluster i when operating in scenario s. This matrix comprehensively shows how each representative design would perform in futures it was not specifically designed for.

Robustness and expected value analysis

Finally, the robustness of each design cluster is quantified and compared using the cost matrix $C_{i,s}$. Two key metrics are employed:

The expected TAC, $E(C_i)$: Calculated as the probability-weighted average cost of the design cluster across all scenarios. This metric is central for a risk-averse decision-maker aiming to optimize for the most likely average outcome.

$$E(C_i) = \sum_{s \in S} w_s \cdot C_{i,s} \tag{2}$$

where w_s is the probability of scenario s.

Cost Uncertainty Band: For a risk-tolerant perspective, the range of outcomes, defined by the minimum and maximum cost $(\min C_{i,s}, \min C_{i,s})$, is crucial. This uncertainty band visualizes the best- and worst-case financial performance, highlighting the potential downside risk associated with each design cluster. A design with a smaller band is more predictable and less risky.

2.3. Price Scenarios and Uncertainty Consideration

This study focuses on long-term uncertainties inherent in energy markets. We begin by identifying a set of key uncertain parameters, denoted by set E. For each uncertain parameter $e \in E$, we define a discrete set of possible future prices, referred to as levels denoted by set L_e (e.g. 'low', 'medium', 'high'). A single scenario, denoted by s, represents one complete and plausible vision of the future. It is constructed as a unique combination of specific levels, one for each uncertain parameter. To systematically explore the full range of possible futures, we generate the complete set of scenarios S using a full factorial combination. For E uncertain parameters and each parameter e has L_e levels, the total number of scenarios is

$$N = \prod_{e \in E} L_e. \tag{3}$$

Assuming all parameters have the same number of levels L, this simplifies to

$$N = L^E. \tag{4}$$

To conduct a probabilistic analysis, we assign a probability $w_{e,l}$ to each level $l \in L_e$ for every parameter $e \in E$. These probabilities represent the decision-maker's belief about the likelihood of a particular price occurring. By adjusting these values, different risk attitudes can be modeled. For the set of probabilities for any given parameter to be valid, they must sum to one. This is expressed formally as:

$$\sum_{l \in L_e} w_{e,l} = 1, \qquad \forall\, e \in E \tag{5}$$

This constraint ensures that for each uncertain parameter e, the defined levels $l \in L_e$ represent a complete set of mutually exclusive outcomes.

The next step is to calculate the joint probability w_s for each complete scenario $s \in S$. An assumption in this methodology is that the uncertain parameters are stochastically independent. This means that the price of one energy carrier is assumed not to influence the price of another. Under this assumption, the joint probability of a scenario s is defined as follows:

$$w_s = \prod_{e \in E} w_{e,l(s)} \tag{6}$$

where $l(s)$ indicates the level corresponding to scenario s for parameter e. As a direct consequence of this formulation, the sum of the joint probabilities of all scenarios in the set S will equal one

$$\sum_{s \in S} w_s = 1 \tag{7}$$

forming a complete and valid probability space for the subsequent analysis. This structured approach provides a flexible methodology for transforming expert opinions or historical data into a discrete set of weighted scenarios, which are essential for the cross-scenario evaluation and resilience analysis steps outlined previously.

3. Model Application

The methodology presented in Section 2 is applied to a specific case study to identify an economically resilient energy system for a residential building in Germany. This section describes the reference building, the technological options, the economic framework, and the specific definition of the uncertainty scenarios that form the basis of the analysis.

3.1. Reference Building and Technology Portfolio

The framework is applied to a representative German single-family house (SFH) located in Potsdam. The building, characteristic of the 1958-1968 construction period, is modeled with two floors and has a heated floor area of 180 m². The building envelope is assumed to meet the EnEV 2016 standard. Weather data, including hourly ambient temperature and solar irradiation for Potsdam, are taken from the German Weather Service [20]. The available technology portfolio for the optimization is as listed in Section 2.1.

3.2. Economic Data and Probability Definition

For the economic evaluation, an analysis period of 15 years starting from 2025 is assumed. All investments and future costs are converted to a present value using an annual discount rate of 2% to determine the TAC. The investment and operational costs, including maintenance and service costs for all technologies, are derived from the German catalogue for municipal heat planning and data from long-term scenarios for the transformation of the energy system in Germany, commissioned by the Federal Ministry for Economic Affairs and Climate Action [21,22]. Additional probable energy carrier prices are defined based on a review of long-term energy scenarios from additional literature such as [23–27]. The assumed energy carrier price scenarios are listed in **Table A.1**.

Applying the methodology described in Section 2.3, the uncertain parameters and their levels for this case study are defined as follows. Four energy carrier prices are identified as the key uncertain parameters with a significant impact on long-term economic viability: (1) household electricity, (2) heat pump electricity, (3) natural gas, and (4) biogas price. To isolate the impact of market volatility from policy-driven costs, this study defines energy carrier prices exclusive of CO_2 prices. While acknowledging the significant potential impact of carbon pricing, this deliberate exclusion avoids confounding the primary focus on market-driven price fluctuations, which are themselves highly uncertain. [24–26,28,29]

For each of these parameters, a set of three discrete levels for the future price trajectory is defined: 'low', 'medium', and 'high'. These price trajectories are based on an analysis of long-term energy studies and are intended to cover a broad spectrum of possible market developments.

The complete set of scenarios is generated using a full factorial combination of these levels. With four uncertain parameters, each having three levels, this results in a total of $N = 3^4 = 81$ unique scenarios. Each scenario thus represents a specific, plausible future of energy market prices and provides the foundation for the subsequent analysis of design resilience and economic performance.

3.3. Scenario Definition and Case Studies

To analyze the effects of uncertainty and different risk attitudes of the decision-maker, a reference case and several case studies are defined. These differ in the probability weighting of the individual price levels and, consequently, in the resulting joint probability of the scenarios. For the presented use cases the energy prices and probabilities are noted in **Table A.1**.

Benchmark case (single forecast): This case represents standard design practice using single forecast optimization. The model is solved only once using the medium price scenario for all four energy carriers. The resulting system design serves as a deterministic reference (baseline) against which the resilient designs, optimized under uncertainty, are compared.

Risk-averse case - equal probability: In this case, we apply the multi-step methodology considering multiple forecast scenarios. Acknowledging the deep uncertainty of long-term forecasts, we assign an equal probability of $1/3$ to each price level (low, medium, high) for every parameter. The joint probability for each of the 81 scenarios is therefore $(1/3)^4 \approx 1.23\%$. The objective is to identify the design cluster with the minimal expected TAC across this uniform probability distribution, while simultaneously evaluating its robustness. Specifically, we seek a design that not only performs well on average but also exhibits low-cost volatility.

Risk-averse case - middle price scenario focus: In this case, we apply the multi-step methodology considering multiple forecast scenarios. Acknowledging the deep uncertainty of long-term forecasts, we assign a probability of 50% to the medium price levels for each energy carrier and 25% for each low and high price scenario of the energy carriers.

Risk-tolerant case - electricity- vs. gas-favorable: To model decision-makers with specific views on the future, we define two risk-tolerant cases. In the 'electricity-favorable' case, we assign a high probability (80%) to scenarios with low electricity prices and high gas prices. Conversely, the 'gas-favorable' case assigns high probability to scenarios with high electricity and low gas prices. These cases allow us to analyze how a biased outlook on future prices influences the optimal design.

4. Results

This chapter presents the results derived from the optimization and clustering framework. The analysis begins by identifying a set of representative design clusters from the 81 scenario-specific optimal solutions. Subsequently, the economic performance and resilience of these design clusters are evaluated across the entire uncertainty space. Finally, the influence of a decision-maker's subjective risk profile on the selection of the optimal design is investigated, demonstrating the practical application of the proposed methodology.

4.1. The Deterministic Baseline vs. Design Clusters

Benchmark design

The benchmark case represents the conventional design approach, where the system is optimized for a single forecast of the future price scenarios. In this study, this corresponds to the 'medium' price scenario for all four energy carriers. The optimization model's objective is to minimize the TAC for this single scenario. The model selects a HP and EH for heat generation, PV for electricity generation and TES and TES-DHW as storages.

The PV system is sized at maximal capacity, primarily to reduce the costs of household and HP electricity, which are significant even in the 'medium' price scenario. A BAT is not found to be economically viable in this deterministic context. For this specific 'medium' scenario, the optimized design achieves a TAC of 8908 €/a.

To evaluate the brittleness of this benchmark design, its performance was subsequently simulated across all 81 uncertainty scenarios. While it performs optimally in the single scenario it was designed for, its economic performance varies in others. When averaged over all 81 equally weighted scenarios, the expected TAC of the benchmark design is 8870 €/a. This is 0.4% lower than its design-point TAC, indicating an accurate estimation of long-term costs. The TAC ranges from a best-case of 6930 €/a (in scenarios with low electricity prices) to a worst-case of 11532 €/a (in scenarios with high electricity prices). This distribution of potential outcomes, particularly the high cost in the worst-case scenario, highlights the significant financial risk associated with a design approach based on single forecast scenarios.

Design clusters

To manage the complexity of 81 unique optimal designs, hierarchical clustering was applied to group them into a manageable set of representative system configurations, or here called design clusters. The optimal number of clusters was determined to be seven, based on the silhouette score, resulting in seven distinct design clusters. Each of the 81 optimal designs corresponds to one of these seven design clusters. **Figure 2** illustrates the frequency of each design cluster, indicating a clear trend in the optimal solutions across the uncertainty space.

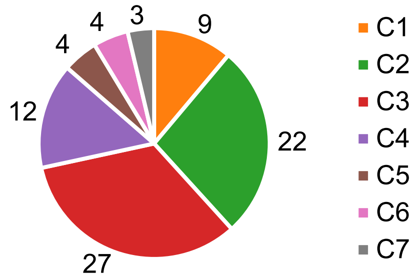

Figure 2. *Number of scenario-based optimal designs represented by each design cluster C.*

Figure 3 details the technological composition of the benchmark case and the seven design clusters. Cell color is normalized by columns (component) to visually highlight a cluster's technological emphasis, while the numerical value states the component's absolute mean capacity. A systematic analysis of these design clusters reveals significant trends in chosen system design. The majority of optimal solutions, representing 70 of the 81 scenarios (over 80%), fall into the all-electric design clusters 1 through 4. These systems are consistently centered around HP, EH, and PV, with variations primarily in the energy storage configuration. Design cluster 1 (C1) represents 9 designs and employs all storage technologies, a TES, a TES-DHW and a BAT. Design cluster 2 (C2) represents 22 designs and is similar to design cluster 1 but excludes the TES-DHW. Design cluster 3 (C3) represents 27 designs, utilizes next to the HP, EH and PV the thermal storages, TES and TES-DHW, whereas design cluster 4 (C4) represents a simpler layout with only a TES. In contrast, the remaining design clusters incorporate fuel-based primary movers. Design clusters 5 (C5) and 6 (C6) are hybrid systems based on a CHP unit supplemented by a smaller HP, with C5 additionally including a BAT. Design cluster 7 (C7) utilizes BOI hybridized with HP, PV, and both thermal and battery storage. A salient observation across all seven design clusters is the ubiquitous selection and maximum sizing of the PV system, underscoring its universal economic viability as a hedge against electricity price volatility. Conversely, STC were not selected in any optimal design, suggesting a lack of competitiveness within the evaluated context.

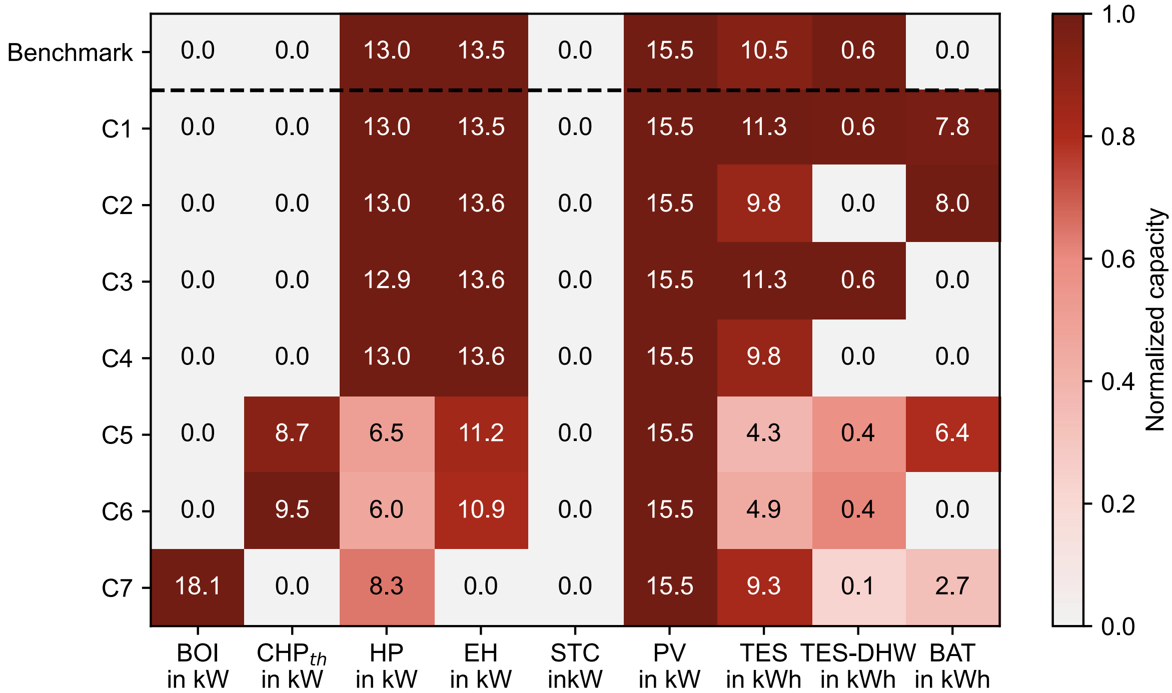

Figure 3. *Mean component capacities (normalized) for each design cluster C.*

Performance and robustness analysis of design clusters:

The economic performance and robustness of the seven design clusters were evaluated across 81 plausible future scenarios, with results presented in **Figure 4**. A primary finding from this analysis is the clear divergence in both performance and risk between the all-electric design clusters (C1-C4) and those incorporating fuel-based technologies (C5-C7). Specifically, the all-electric clusters consistently exhibit a lower mean and median TAC, suggesting that, on average, they represent the more cost-effective solution across the spectrum of potential futures.

Furthermore, the clusters differ starkly in their cost volatility and associated economic risk. The all-electric designs show a significantly smaller interquartile range and overall cost deviation, a narrow distribution that signifies high robustness and cost predictability, making them less sensitive to volatile energy markets. In contrast, the fuel-based clusters (C5-C7) display a much wider cost distribution. The CHP systems (C5 and C6) show numerous high-cost outliers reaching up to 17000 €/a, indicating a high-risk profile and strong vulnerability to unfavorable market conditions. This is reflected in their right-skewed cost distributions, where the mean is pulled significantly above the median by these costly scenarios. Within these groups, the cost distributions for clusters C1/C2, C3/C4, and C5/C6 are similar. The relationship between the mean and median reveals important skewness. For clusters C3 and C4, the mean is slightly higher than the median, indicating a right-skewed distribution where a minority of high-cost scenarios pull the average up.

Figure 4 provides deeper insight into the scenarios for which the individual designs were optimized by plotting the original TAC of the design point against the overall distribution. The position of this point provides information about the inherent robustness of the design under a given scenario. For several clusters (C2, C4, C5, and C6), the design point lies at or near the minimum of their TAC distribution. This means they have been optimized for extremely favorable best-case scenarios. While they perform excellently under these specific conditions, they incur higher costs in less favorable scenarios and underestimate costs. In contrast, C1 exhibits the characteristics of a robust design, as its design point lies near the maximum of its TAC distribution. This is an example of a system optimized for pessimistic conditions, so that it delivers acceptable performance even under these worst-case conditions compared to alternative designs. This design offers a reliable upper bound on costs while also providing potential savings in more favorable scenarios. Between these extremes lie the balanced designs C3 and C7, which are designed for more average scenarios and whose design points lie near the center of their respective distributions.

The individual markers in **Figure 4** illustrate the scenario-dependent strengths of each design by showing the performance of that design across all clusters. For example, the CHP-based designs (C5, C6) achieve their most economical configuration in scenarios characterized by high electricity prices and low fuel prices (represented as a pink triangle or blue circle markers), while this scenario leads to a higher TAC for other designs. Conversely, these scenarios result in increased TAC for alternative designs. In contrast, the all-electric designs demonstrate superior performance at high fuel prices, as they are unaffected by fluctuations in the fuel market (e.g. purple plus marker).

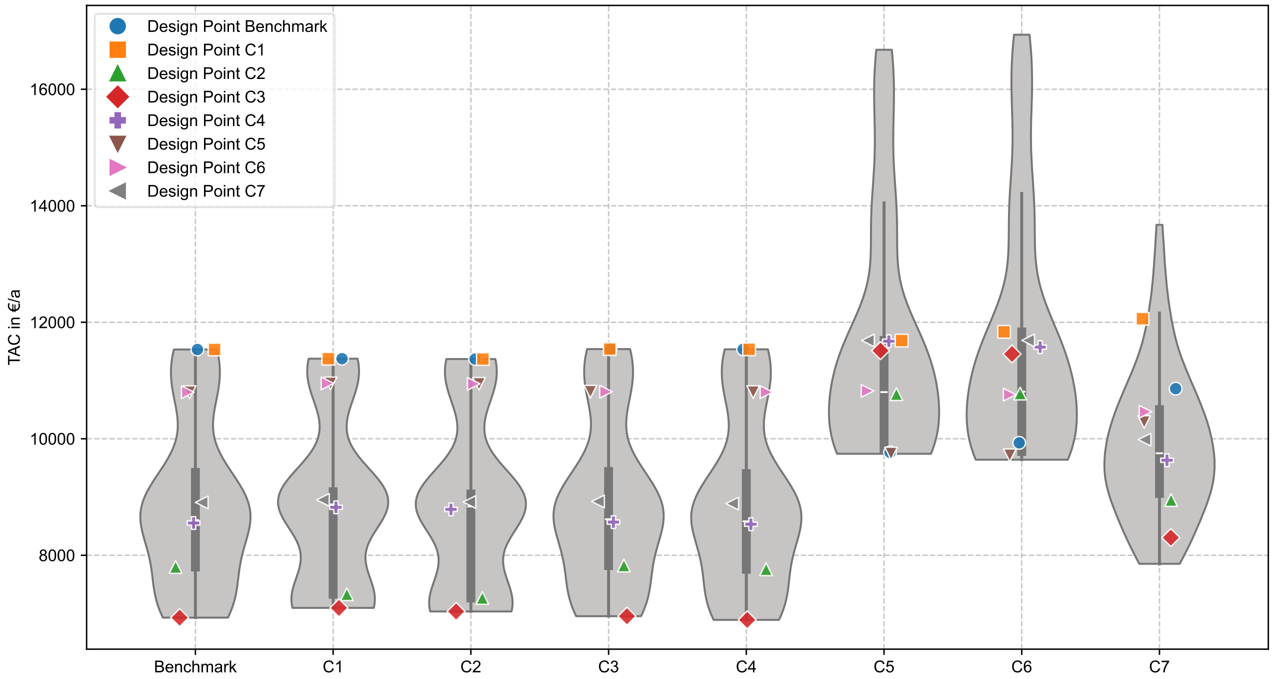

Figure 4. *Economic performance and risk profile of each design cluster C are presented in a smoothed density function of TAC with overlayed design points. The distribution of TAC across all 81 scenarios reveals the trade-off between expected cost and robustness. For each cluster, the violin plot displays the median cost (horizontal white line), the interquartile range (gray bar), and the full range of outcomes (whiskers). The TAC of the design point scenario of the benchmark and each design cluster C is marked by points over all designs, so that the designs can be compared to each other based on the same scenarios. A cluster with a lower median is more profitable on average, while a shorter violin plot signifies a more robust design with more predictable costs.*

Impact of subjective price expectations

The final stage of the analysis investigates how optimal design choice is influenced by the incorporation of subjective beliefs about future energy price trajectories. The Expected TAC was calculated for a representative subset of design clusters (C2, C4, C5, and C7) under four distinct probability weighting schemes, as described in Section 3.3, representing different risk profiles and market outlooks. The results are depicted in **Figure 5**.

For a risk-averse decision-maker assuming equal probability for all scenarios, or for a conservative decision-maker focusing on middle price developments, the all-electric design clusters 2 and 4 are unequivocally superior, offering the lowest expected TAC. This finding reinforces the conclusion from the previous analysis that electricity-based system represents the most prudent strategy from a balanced perspective, as it also increases the degree of self-sufficiency. However, for a risk-tolerant decision-maker convinced of a future with low and stable gas prices (gas-favorable scenario), the economic evaluation shifts. In this case, fuel-based design clusters 7 becomes a competitive alternative, and design cluster 5 achieves its lowest expected TAC, illustrating a rational, justification for a fuel-based investment. Conversely, in the future anticipated to have low electricity prices, design clusters 2 and 4 further solidify their dominance, delivering substantial expected cost savings over any fuel-based system.

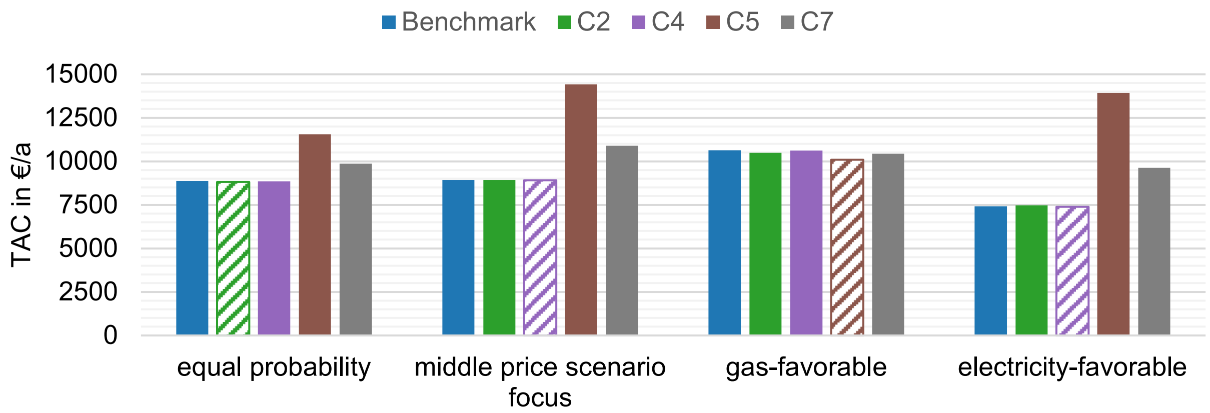

Figure 5. *Case study based expected TAC for selected design clusters C. Pattern indicates the minimal bar of the respective case.*

A comparison between the benchmark case and the design clusters tells that for the considered case study, the identified design clusters can lead to up to 1% lower expected TAC compared to the benchmark. At the same time, the design clusters would lead to different CAPEX, e.g. 12% higher for C2 and 2% lower for C4 compared to the benchmark CAPEX. This highlights a crucial trade-off between initial investment and long-term security. Specifically, the all-electric systems (C1-C4) justify their investment by providing enhanced resilience, showing up to 7% lower cost volatility than the benchmark, as illustrated by the narrower cost distribution in **Figure 4**. The results demonstrate that while fuel-based systems may offer advantages in specific, favorable futures, all-electric systems featuring a heat pump, PV, and storage represent the most robust and economically resilient investment across a wide and uncertain range of long-term scenarios.

5. Discussion

This study was motivated by a gap in building energy system design: conventional methods rely on deterministic, single-forecast optimizations that fail to account for long-term economic uncertainties, exposing building owners to significant financial risk. While stochastic methods exist, a practical approach for identifying economically resilient designs at the individual building level, across a portfolio of technologies and multiple uncertainties, has been lacking. This paper introduced a multi-step methodology to address this gap, aiming to distinguish not just optimal but robust system configurations.

The application of this methodology yielded several key findings. First, from a complex solution space of 81 unique, scenario-specific optimal designs, a set of seven distinct design clusters emerged. This consolidation reveals that despite price uncertainties, the set of economically rational system designs is finite and classifiable. Second, a technological trend was observed: all-electric design clusters, centered around a HP and PV system, represented over 80% of the optimal solutions. The universal selection and maximum sizing PV systems across all clusters underscores its role as a core component. Third, fuel-based systems, while optimal in niche scenarios, were found to carry significantly higher economic risk.

Our findings provide an economic rationale for Europe's decarbonization strategy, demonstrating that all-electric (HP+PV) systems are economically resilient. The PV system acts as a financial hedge against volatile grid prices, while storage technologies like batteries enhance this resilience by maximizing self-consumption. This aligns with prior techno-economic studies confirming the benefits of PV-battery systems for increasing self-sufficiency and hedging against price risk [30,31].

A detailed examination identifies the all-electric design cluster 2 (HP, EH, PV, TES, and BAT) as the most robust configuration. Its resilience stems from the inclusion of a battery. While the battery contributes to a modest reduction in the expected TAC (approximately 1% compared to the benchmark), its primary value lies in risk mitigation. By enabling greater self-consumption, the battery shields the system from high prices in the electricity market, which is reflected in cluster 2 having the lowest maximum TAC across all 81 scenarios

(11369 €/a), offering protection against worst-case financial outcomes. This positions design cluster 2 as the most economically resilient design within the study's parameters, optimally balancing expected cost with potential adverse outcomes.

A further critical insight from the analysis is the existence of a flat optimum, where multiple, structurally different design clusters yield very similar expected economic outcomes. For instance, the all-electric clusters (C1-C4) exhibit closely grouped expected TAC despite variations in their storage configurations. This finding is significant because it implies that there is no single, unequivocally superior solution. Instead, the decision-maker is presented with a portfolio of near-optimal, resilient designs. The final choice between them may then be guided by secondary criteria not captured in the economic model, such as upfront investment cost (CAPEX), perceived maintenance complexity, or a qualitative preference for maximum energy self-sufficiency. This reinforces the value of our methodology not as a tool that dictates a single answer, but as a decision-support instrument that illuminates a set of robust choices.

The findings of this study should be interpreted in light of several key limitations that frame the results and guide future work. First, the energy system model employs certain simplifications inherent to this type of analysis. For instance, the photovoltaic model assumes optimal panel orientation and does not account for suboptimal, geometric realities of individual buildings (e.g. roof pitch, shading). This may overstate PV yields and the corresponding economic attractiveness of all-electric designs. Similarly, the model relies on simplified linear component efficiencies, thereby neglecting real-world complexities such as part-load performance, which could influence operational costs. Second, the scope of the uncertainty analysis, while central to the study, is necessarily bounded. The 81 scenarios represent a discrete set of possible futures and may not capture extreme events plausible in the current geopolitical climate. Therefore, the identified robust designs are robust only with respect to the uncertainties considered. Moreover, the analysis focused on energy price uncertainty, omitting other significant volatile factors such as CO_2 pricing, which is expected to become an increasingly dominant cost driver and could further penalize fossil-fuel systems. Finally, the generalizability of the results is constrained. The analysis is specific to a SFH typology in a single German climate zone. The applicability of the identified robust design clusters to other building types, or different climatic and market contexts remains to be confirmed.

These limitations provide direct guidance for future research approaches. To enhance the model's realism, future work should incorporate more detailed building models that account for specific roof geometries and shading, providing more conservative and site-specific PV yield estimations. Expanding the scope of uncertainty to include CO_2 price developments is a critical next step for a more holistic risk assessment. Furthermore, testing the scalability of the methodology by applying it to a diverse range of building typologies and larger, multi-building energy systems. Such analysis, conducted across various climate regions, would be invaluable for validating the broader applicability of the identified design clusters and the methodology itself.

In summary, this discussion has interpreted the emergence of distinct, resilient design clusters from a highly uncertain decision-making environment. By synthesizing the results, we have demonstrated that an all-electric configuration combining HP, PV, and storages represents the most economically robust investment strategy, effectively hedging against volatile energy markets. The presented analysis confirms that a shift in design philosophy from seeking a single optimum to identifying system-level resilience is essential for navigating the energy transition.

6. Conclusion

This paper addressed the challenge of designing economically resilient building energy systems under long-term uncertainties in energy markets. We developed and applied a practical, multi-step methodology that moves beyond the limitations of traditional design practices based on single, deterministic forecasts. The approach integrates scenario-specific optimization, hierarchical clustering to identify representative design clusters, and a comprehensive cross-scenario evaluation to systematically quantify both economic performance and financial risk.

The application of this methodology to a representative German single-family house yielded a central, unambiguous finding: all-electric design clusters, centered on a heat pump and a photovoltaic system, are the most resilient configurations across a wide range of plausible future energy market conditions. The analysis highlights the critical role of photovoltaic as a financial hedge against electricity price volatility. Specifically, the design combining a heat pump, photovoltaic, and a battery emerged as the most resilient, offering the lowest expected cost while effectively capping downside risk in worst-case scenarios. Crucially, the methodology moves beyond a single point-solution by quantifying performance under risk. While a conventional optimization might coincidentally recommend a similar design, it leaves the decision-maker blind to the financial exposure in alternative futures.

Ultimately, this research demonstrates that a fundamental shift in design philosophy beyond single-forecast optimization, from seeking a single optimal solution to identifying system-level resilience, is not only feasible but essential for making sound long-term investments in the building sector. The proposed methodology serves as a valuable and transparent decision-support tool, enabling stakeholders to identify system designs that are not just cost-effective for an assumed future, but economically resilient against the uncertain one.

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Appendix A

Table A.1. *Energy carrier price scenarios for the use cases and assumed probabilities.[23–27]*

energy carrier	scenario level	price in €/kWh	probabilities				
			benchmark	equal	middle price scenario	electricity-favorable	gas-favorable
household electricity	high	0.437	0	0.123	0.25	0.1	0.1
	middle	0.315	1	0.123	0.50	0.1	0.1
	low	0.231	0	0.123	0.25	0.8	0.8
heat pump electricity	high	0.325	0	0.123	0.25	0.1	0.1
	middle	0.229	1	0.123	0.50	0.1	0.1
	low	0.144	0	0.123	0.25	0.8	0.8
natural gas	high	0.209	0	0.123	0.25	0.8	0.1
	middle	0.106	1	0.123	0.50	0.1	0.1
	low	0.074	0	0.123	0.25	0.1	0.8
biogas	high	0.209	0	0.123	0.25	0.8	0.1
	middle	0.150	1	0.123	0.50	0.1	0.1
	low	0.090	0	0.123	0.25	0.1	0.8

Nomenclature

Latin symbols

C	cost matrix, €/a
$CAPEX$	annualized expenditures, €/a
$E(C)$	expected TAC, €/a
K	number of representative design clusters
$OPEX$	annual operational expenditures, €/a
N	number of distinct scenarios
TAC	total annualized cost (TAC), €/a
w	probability

Subscripts and superscripts

$e \in E$	set of uncertain energy carrier prices
i	design cluster
$l \in L$	set of energy carrier price levels
$s \in S$	set of energy price scenarios
$t \in T$	portfolio of available technologies

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