

Article

Life-Cycle Cost–Optimal Right-Sizing and Replacement Assessment of Distribution Transformers Under Demand Uncertainty

Jorge Muñoz-Pilco , Milton Ruiz , Cristian Cuji  and Edwin García 

Smart Electric Grids Research Group GIREI (Spanish Acronym), Salesian Polytechnic University, Quito 170702, Ecuador; mruizm@ups.edu.ec (M.R.); ccuji@ups.edu.ec (C.C.); egarcia@ups.edu.ec (E.G.)

* Correspondence: jmunoz@ups.edu.ec

Abstract

This paper presents a scenario-based optimization framework for evaluating the life-cycle cost of right-sizing and replacement timing for distribution transformers under demand–growth uncertainty. The proposed formulation jointly considers the discrete commercial transformer ratings, the discounted investment cost, and the monetized iron and copper losses over a 15-year planning horizon. Demand uncertainty is represented by nine scenarios defined by combinations of initial apparent power demand and annual growth rate, with $D_1 \in \{45, 50, 55\}$ kVA and $g \in \{3\%, 4\%, 5\%\}$. Under these assumptions, the demand envelope evolves from an initial range of 45–55 kVA to approximately 68.1–108.9 kVA in Year 15, while expected demand increases from 50 kVA to about 87 kVA. The optimization results show that the economically optimal policy is to install a 112.5 kVA transformer in Year 1 and maintain that rating throughout the horizon, without triggering any replacement events. The selected transformer maintains expected loading between approximately 0.44 p.u. and 0.77 p.u., while the upper-demand scenario remains below 1.0 p.u. over the entire horizon. These results indicate that, for the demand–growth conditions analyzed, the preferred outcome is a single initial sizing decision rather than a phased replacement strategy. Therefore, the proposed framework provides a consistent scenario-based alternative to deterministic margin-based planning for distribution transformer asset management.

Keywords: distribution transformers; power distribution planning; asset management; life-cycle cost; optimization; uncertainty; load modeling; decision making

1. Introduction

Distribution transformers (DTs) are among the most widespread assets and require the largest capital investment in distribution systems, directly affecting technical losses, reliability, and long-term operating expenses. The conventional sizing and renewal of distribution transformers has often been justified by deterministic engineering margins; however, this practice can lead to systematic oversizing (unnecessary capital expenditure and no-load losses) or undersizing (overloads, accelerated insulation aging, and reliability degradation). As a result, public utilities are increasingly employing economic criteria based on the life cycle, such as the total cost of ownership (TCO) and the life-cycle cost (LCC), in which losses and other life-cycle cost components may be monetized [1–4].

This decision-making framework has been further complicated by the uncertainty surrounding demand growth driven by the electrification of certain sectors, e.g., transportation, distributed generation, and flexible demand. Empirical evidence indicates that



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load behavior and local adoption patterns may differ significantly from simplified forecasts, increasing uncertainty at the transformer level [5]. At the same time, several studies have shown that peaks driven by electric vehicles and power quality and ambient temperature conditions can significantly increase transformer lifetime loss unless mitigation measures are applied (e.g., scheduling and PV/BESS support) [6–8]. These trends are driving planning methods that go beyond simple static sizing, incorporating uncertainty, aging, and flexible operational alternatives.

The most recent literature has advanced DT planning from multiple angles, including the following:

- Optimal transformer design and selection from a TCO/LCC perspective [9–11];
- Dynamic and constraint-aware component classification to free up short-term capacity, respecting thermal and current constraints [12,13];
- Asset management formulations that consider relocation and economic trade-offs across the network [14,15];
- Replacement prioritization frameworks based on health/risk indices for transformer fleets [16–19].

Despite these advances, a practical gap remains in distribution transformer planning. Many studies on transformer selection and life-cycle cost focus on design or rating choice under deterministic loading assumptions, whereas many replacement-oriented models assume fixed transformer capacities, exogenous upgrade logic, or simplified load trajectories. As a result, the coupled planning problem of selecting a commercial transformer rating and determining whether replacement should occur under uncertain long-term demand growth is still insufficiently addressed in a transparent and reproducible way.

This paper addresses that gap by proposing a scenario-based optimization framework for the joint assessment of transformer right-sizing and replacement timing under demand–growth uncertainty. The formulation combines (i) discrete commercial transformer ratings; (ii) discounted investment, iron-loss, and copper-loss costs; and (iii) a finite scenario set representing alternative initial demand and growth conditions over the planning horizon. In addition to obtaining a cost-optimal capacity path, the proposed workflow is explicitly structured to make the assumptions on scenario construction, discounting, loss monetization, and adequacy verification reproducible and extensible for future planning studies.

The remainder of the paper is organized as follows. Section 1 reviews the literature on transformer planning based on life-cycle cost, replacement strategies, and demand–growth uncertainty and summarizes the positioning of the present study. Section 2 describes the proposed materials and methods, including the cost model, scenario construction, decision variables, constraints, and optimization workflow. Section 3 presents the numerical results for the case study and complementary sensitivity analyses. Section 4 discusses the findings, limitations, and implications for asset planning. Finally, Section 5 summarizes the main conclusions.

1.1. Literature Review

1.1.1. Transformer Selection Based on LCC/TCO and Eco-Efficiency

The economic approach to transformer selection has long been based on TCO, in which acquisition cost is combined with the deferred costs of no-load and load losses [1]. Subsequent studies extended this perspective by incorporating environmental externalities and carbon-related impacts, reinforcing the case for efficient transformer selection from a broader regulatory and societal perspective [2,3]. More recent work has revisited LCC formulations with expanded cost structures and modern optimization techniques, while transformer design studies have introduced multi-objective and heuristic formulations that explicitly account for power losses and total ownership cost [4,10,11,20].

However, most of these contributions remain centered on transformer selection or design rather than on the coupled long-horizon planning problem in which transformer capacity must be selected from a discrete commercial catalog while replacement timing is also evaluated under uncertain demand growth. In other words, they improve the economic assessment of candidate transformers, but they do not generally formulate right-sizing and replacement timing as a joint planning decision under explicit scenario-based uncertainty.

1.1.2. Dynamic Classification, Capacity Deferral, and Thermal Constraints

With increasing peak demand and variability introduced by distributed energy resources, dynamic-capacity approaches have attracted attention. Dynamic transformer rating (DTR) methods quantify admissible loading based on thermal and current limits, allowing for short-term capacity to be released without immediate reinforcement [12]. Related work has also explored dynamic component classification to increase transformer hosting capacity while maintaining operational security [13].

These approaches are highly relevant because they create opportunities for operational deferral of investment. Nevertheless, they are primarily operational in nature: they quantify short-term admissible loading or flexibility margins, but they do not usually solve the long-term planning problem of selecting a commercial transformer size and determining replacement timing under uncertain multi-year demand trajectories. Thus, they complement asset planning but do not substitute for it.

1.1.3. Impacts of Electrification and Flexible Resources on Transformer Aging

The growing penetration of electric vehicles introduces stochastic charging behavior that can accelerate transformer aging and increase the risk of service disruption [6,8]. A broad set of mitigation measures has therefore been studied, including coordinated charging, photovoltaic support, battery storage, curtailment, and other local flexibility mechanisms [7,21–26]. These measures can reduce thermal stress and postpone upgrades, which makes them highly relevant for transformer planning.

However, much of this literature treats transformer capacity as fixed and focuses on operational mitigation once the asset is already in place. As a consequence, these studies provide valuable insight into aging management and upgrade deferral, but they do not generally address the coupled decision of whether a different initial transformer size should be selected and whether later replacement remains economically justified under uncertain long-term demand evolution.

1.1.4. Asset Management, Reliability, Relocation, and Replacement Planning

Beyond sizing, distribution transformer management also encompasses relocation, reliability assessment, and replacement prioritization. Integer programming approaches have been proposed for transformer relocation under practical labor and network constraints, later extended toward broader economic asset management formulations [14,15]. Reliability-oriented models quantify the effects of load transfer and spare sharing on transformer and station reliability indices [27–29], while replacement planning has also been linked to demand-response effects [30]. At the fleet level, health-index and risk-based methodologies provide useful prioritization criteria for large transformer populations [16–18,31].

Although these studies are highly relevant for utility asset management, their main focus is usually not the joint optimization of transformer right-sizing and replacement timing for a single planning case under explicit demand-growth uncertainty. In most cases, replacement is prioritized, scheduled, or economically screened given pre-existing capacity assumptions rather than being co-optimized together with the initial transformer size.

1.1.5. Data-Driven Transformer Load Estimation and Its Importance for Planning Uncertainty

Accurate planning at the transformer level requires sufficiently granular knowledge of load, which is increasingly enabled by AMI, smart-meter data, and geospatial association methods. Studies on kVA estimation from smart-meter measurements and on transformer-to-meter association improve observability and reduce planning errors [32,33]. In parallel, data-quality studies have shown that faulty or incomplete information can materially affect asset management decisions [34].

These contributions are important because they strengthen the data layer that supports planning. However, improved observability by itself does not provide a full planning model. What is still needed is a decision framework that translates uncertain demand information into transparent sizing and replacement decisions while making the scenario assumptions and economic criteria used in the evaluation explicit.

1.1.6. Synthesis and Position of This Article

Table 1 shows that the existing literature tends to emphasize one of four perspectives: (i) TCO/LCC-based transformer selection and design; (ii) operational mitigation of thermal stress through flexibility or dynamic rating; (iii) relocation, reliability, and fleet-level asset management; or (iv) data and observability improvements for transformer-level planning. The present study is positioned at the intersection of these streams but with a narrower and more explicit planning objective: to jointly evaluate the selection of a discrete commercial transformer rating and the timing of possible replacement under uncertain demand growth using a consistent life-cycle cost framework.

Table 1. Representative literature on distribution transformer sizing, rating, asset management, and replacement planning.

Reference	Scope/Decision	Method Focus	Typical Limitation w.r.t. This Paper
[1]	DT investment evaluation (TCO)	Decision-support TCO with loss monetization	Deterministic load; no explicit replacement timing optimization
[2,3]	DT selection with environmental cost	TCO/LCC extended with externalities	Selection-centric; limited co-optimization of timing and size
[4,20]	Transformer LCC modeling/forecasting	LCC models + optimization/prediction	LCC without joint right-sizing + replacement timing under uncertainty
[10,11]	DT design optimization (TCO-aware)	Multi-objective/heuristic optimization	Design-centric; planning horizon decisions not addressed
[12,13]	DT dynamic rating/hosting capacity	Thermal-current constraints; dynamic rating	Primarily operational; replacement timing and right-sizing not optimized
[6,8]	EV impacts on DT aging/reliability	Probabilistic aging assessment; mitigation analysis	Mitigation studied, but DT sizing/replacement decisions often fixed
[21,35,36]	Flexibility/storage to defer upgrades	Storage/curtailment planning coupled to DT constraints	Often focuses on operational deferral, not replacement timing + capacity choice
[14,15]	DT relocation and asset management	Integer/MILP formulations with practical constraints	Relocation-centric; does not jointly optimize replacement timing + right-sizing under growth uncertainty
[27–29]	DT reliability assessment	Load transfer/spare sharing reliability indices	Reliability metrics not integrated into an LCC right-sizing + timing framework
[30]	Replacement planning with DR effect	Long-term planning considering DR	Typically assumes fixed DT sizing choices or simplified uncertainty handling
[16–18]	Fleet replacement strategies/reviews	Health/risk-index and replacement prioritization	Prioritization rather than joint, scenario-based optimization of timing and size
[32–34]	DT observability and data quality	AMI-based estimation/mapping; data quality impacts	Data layer improved, but not a full joint timing + size optimization under uncertainty

Accordingly, the contribution of this article is not to replace the existing strands of transformer research but to connect them through a reproducible scenario-based planning workflow. The proposed approach is intended as a transparent baseline for medium-term asset planning, one that can later be extended toward richer uncertainty representations, explicit thermal-aging models, and coordinated flexibility resources.

2. Materials and Methods

2.1. Inputs and Planning Assumptions

This study addresses a medium-term strategic planning problem for distribution transformers, aimed at defining a single capacity-selection and replacement policy under demand–growth uncertainty. Accordingly, the formulation is intended for long-horizon asset planning rather than short-term operational dispatch or thermal real-time control [37,38].

The baseline planning horizon is set to 15 years. This value is not intended to represent the full technical lifetime of the transformer, which may extend to 20–40 years depending on operating and environmental conditions, but rather an economically and operationally meaningful decision horizon for distribution planning, within which demand projections remain tractable and replacement decisions can be consistently evaluated in present-value terms [37–39].

To preserve tractability and align the model with strategic planning practice, time is discretized in annual periods. Therefore, the formulation captures long-term investment and loss trade-offs, but it does not aim to reproduce sub-hourly thermal transients, seasonal thermal cycles, or detailed operational loading dynamics [12,39,40].

We consider the long-term planning of distribution transformers supplying aggregated demand. The planning horizon is discretized into annual periods $t \in \mathcal{T} = \{1, \dots, T\}$ (baseline $T = 15$ years). The decision is to select the transformer rating in service each year (right-sizing) and determine when capacity upgrades occur (replacement timing) to minimize life-cycle cost (LCC) under demand–growth uncertainty.

A catalog of commercial transformer alternatives is defined as $\mathcal{K}$. Each candidate $k \in \mathcal{K}$ is characterized by: nominal capacity S_k (kVA), investment cost C_k^{inv} (USD), no-load (core/iron) losses P_k^{fe} (W), and load (copper) losses at rated load P_k^{cu} (W).

Economic inputs include the discount rate r (1/year), the energy price c_E (USD/kWh), and the capacity price c_P (USD/kW-year). For loss-energy aggregation, we use a load-loss factor f_{loss} (dimensionless), described below.

In the reference case study, economic and technical parameters are adopted as representative planning values for the distribution analysis in Ecuador, including the discount rate, the price of energy, the price of capacity, the transformer catalog, and assumptions regarding loss factors. These parameters are not intended to be universal constants but rather define a calibrated reference case for methodological evaluation and can be replaced when specific data from another geographic area are available [4,39].

2.2. Demand–Growth Uncertainty and Scenario Set

Demand uncertainty is represented through a finite scenario set constructed as the Cartesian product of three representative initial-demand levels and three representative annual growth rates. The objective of this design is not to emulate the full stochastic richness of real load evolution but to provide a transparent and reproducible scenario-based planning structure that captures low, central, and high trajectories of transformer demand over the planning horizon [37,38].

In the baseline case, the initial apparent power demand is defined as $D_1 \in \{45, 50, 55\}$ kVA and the annual growth rate as $g \in \{3\%, 4\%, 5\%\}$. The central values (50 kVA, 4%) represent the reference planning condition, while the lower and upper values define symmetric

deviations around that baseline. This yields nine scenarios, which were considered sufficient for a first-order strategic assessment of capacity adequacy and life-cycle cost without imposing an excessive computational burden or introducing poorly supported probabilistic detail [30,40].

Scenario probabilities are defined by Equation (1), where $\pi_{i,j}$ is the probability assigned to the scenario resulting from the combination of initial-demand level i and annual growth level j , π_i^D is the marginal probability of the i -th initial-demand level, and π_j^g is the marginal probability of the j -th annual growth level.

$$\pi_{i,j} = \pi_i^D \pi_j^g, \quad \pi^D = [0.25, 0.50, 0.25], \quad \pi^g = [0.25, 0.50, 0.25]. \quad (1)$$

For notational convenience, each pair (i, j) is mapped to a scenario index $s \in \mathcal{S}$, so that the corresponding joint probability is denoted by π_s in the optimization model. Scenario probabilities are obtained as the product of two symmetric marginal discrete distributions, one for initial demand and one for annual growth rate. Thus, the central case receives the highest probability, while corner scenarios receive lower weights. This construction explains the probability vector used in the numerical study and preserves consistency between the scenario design and the expected-cost objective function.

The annual apparent power demand trajectory under each scenario is modeled by Equation (2), where demand evolves from a scenario-specific initial level according to a constant annual growth rate over the planning horizon.

$$D_{s,t} = D_{s,1}(1 + g_s)^{t-1}, \quad \forall s \in \mathcal{S}, \forall t \in \mathcal{T}. \quad (2)$$

In Equation (2), $D_{s,t}$ is the apparent power demand in scenario s at year t (kVA), $D_{s,1}$ is the initial apparent power demand of scenario s (kVA), g_s is the annual demand growth rate of scenario s (1/year), and t is the annual time index.

The adopted scenario set captures uncertainty in the initial-demand level and in the long-term annual growth trend. However, it does not explicitly represent intrayear variability, seasonal patterns, saturation effects, abrupt structural breaks, or the endogenous impact of flexible resources such as EV charging control, storage, or distributed generation. Therefore, the present uncertainty model should be interpreted as a planning-oriented approximation of long-term demand envelopes rather than as a detailed stochastic load forecast [5,32].

All annual costs are converted to present value using the discount factor defined in Equation (3) where DF_t is the present-value discount factor associated with year t and r is the annual discount rate.

$$DF_t = \frac{1}{(1+r)^t}, \quad \forall t \in \mathcal{T}. \quad (3)$$

2.3. Life-Cycle Cost Components (Investment + Losses)

The LCC comprises investment costs and monetized losses (iron and copper) [4,41]. The investment is applied when a transformer option is installed (initial installation or replacement). The discounted investment coefficient is defined in Equation (4), where $C_{k,t}^{\text{inv}}$ is the discounted investment cost (USD) of installing option k at year t , C_k^{inv} is the purchase/installation cost (USD), and DF_t is the discount factor from Equation (3):

$$C_{k,t}^{\text{inv}} = C_k^{\text{inv}} DF_t, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}. \quad (4)$$

No-load (iron) losses are approximately constant with load. Their annual monetized cost is defined in Equation (5), where $C_{k,t}^{\text{fe}}$ is the discounted annual cost (USD) of iron losses for option k at year t , P_k^{fe} is iron losses in watts, c_P is the annual capacity price

(USD/kW-year), c_E is the energy price (USD/kWh), 8760 is the number of hours per year, and DF_t is defined by Equation (3). The factor $\frac{1}{1000}$ converts W to kW.

$$C_{k,t}^{\text{fe}} = \frac{P_k^{\text{fe}}}{1000} (c_P + 8760 c_E) DF_t, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}. \quad (5)$$

Copper losses scale approximately with squared loading. The per-unit loading ratio is defined in Equation (6), where $\lambda_{s,k,t}$ is the loading ratio (p.u.) of option k under scenario s at year t , $D_{s,t}$ is the scenario demand from Equation (2) (kVA), and S_k is the transformer nominal capacity (kVA).

$$\lambda_{s,k,t} = \frac{D_{s,t}}{S_k}, \quad \forall s \in \mathcal{S}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}. \quad (6)$$

To monetize copper-loss energy consistently when only annual demand information is available, we use a load-loss factor f_{loss} . If a load factor F_{load} is available (ratio of average to peak demand), Equation (7) can be used:

$$F_{\text{load}} = \frac{D^{\text{avg}}}{D^{\text{peak}}}. \quad (7)$$

In Equation (7), F_{load} is the load factor (dimensionless), D^{avg} is average demand (kVA), and D^{peak} is peak demand (kVA).

In this work, Equation (8) is used as a practical planning approximation to relate load factor and loss factor when detailed feeder load curves are not available. A baseline calibration coefficient of $A = 0.3$ is adopted for the reference case study. Under this calibration, a representative load factor around $F_{\text{load}} \approx 0.62$ yields $f_{\text{loss}} \approx 0.45$, which is used here as a planning value for annual loss monetization [4,41].

$$f_{\text{loss}} = A F_{\text{load}} + (1 - A) F_{\text{load}}^2, \quad (8)$$

Accordingly, the value $f_{\text{loss}} = 0.45$ should be interpreted as a representative planning parameter for annual loss monetization, not as a feeder-specific measured quantity. When hourly or AMI-based load data are available, both A and f_{loss} should be recalibrated from the observed load profile [32,33].

Using Equations (6) and (8), the annual discounted copper-loss cost is modeled by Equation (9):

$$C_{s,k,t}^{\text{cu}} = \frac{P_k^{\text{cu}}}{1000} (\lambda_{s,k,t})^2 (c_P + 8760 c_E f_{\text{loss}}) DF_t, \quad \forall s \in \mathcal{S}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}. \quad (9)$$

In Equation (9), $C_{s,k,t}^{\text{cu}}$ is the discounted annual copper-loss cost (USD) of option k under scenario s at year t , P_k^{cu} is the copper losses at the rated load (W), $\lambda_{s,k,t}$ is the loading ratio from Equation (6), f_{loss} is the loss factor from Equation (8), and (c_P, c_E, DF_t) are as defined above.

Although transformer thermal aging is a critical determinant of asset lifetime, the baseline optimization model does not explicitly internalize hot-spot temperature dynamics, equivalent aging acceleration factors, or insulation loss-of-life equations. This is because the present formulation operates with annual time steps and aggregated demand trajectories, which are appropriate for strategic planning but insufficient for detailed thermal-operational simulation [12].

Recent thermo-economic studies based on IEEE Std C57.91-2011 and IEC 60076-7:2018 show that explicit thermal-aging assessment requires sub-hourly load profiles, ambient temperature trajectories, and transformer-specific thermal parameters. Therefore, in the

present work, thermal aging is not modeled endogenously; instead, loading adequacy and annualized loss costs are used as aggregate planning proxies. An explicit thermo-economic extension based on IEEE/IEC hot-spot and accelerated-aging models is considered a natural next step of the framework [42,43].

2.4. Scenario-Based Optimization Model

The optimization model is formulated as a scenario-based single-policy planning problem. The binary decision variables are scenario-independent, meaning that the model seeks one here-and-now capacity path to be implemented across the planning horizon, while uncertainty is incorporated through the scenario set in the objective-function evaluation and adequacy verification [37,38].

Accordingly, the formulation should not be interpreted as a full multi-stage stochastic program or as a strict robust-optimization model. Instead, it represents a conservative scenario-feasible planning baseline in which a unique capacity policy is selected and then evaluated under all demand trajectories considered [30,40].

Equation (10) enforces that exactly one transformer option must be active in each year of the planning horizon, where $y_{k,t}$ is a binary variable equal to 1 if transformer option k is in service in year t and 0 otherwise.

$$\sum_{k \in \mathcal{K}} y_{k,t} = 1, \quad \forall t \in \mathcal{T}. \quad (10)$$

Adequacy must hold for all scenarios (conservative; baseline), as expressed in Equation (11), where $D_{s,t}$ is the scenario demand from Equation (2), S_k is the capacity of option k , and $y_{k,t}$ selects the in-service option.

$$D_{s,t} \leq \sum_{k \in \mathcal{K}} S_k y_{k,t}, \quad \forall s \in \mathcal{S}, \forall t \in \mathcal{T}. \quad (11)$$

Equation (11) imposes adequacy for all scenarios and all years of the planning horizon. This choice is intentional and reflects a conservative planning criterion aimed at avoiding undersizing in the presence of uncertain demand growth. In practical terms, the formulation privileges technical feasibility across the considered demand envelope over lower-cost policies that might become infeasible in upper-demand trajectories.

Alternative formulations based on probabilistic adequacy, controlled overload risk, or risk-weighted recourse decisions may produce less conservative solutions. However, such approaches require additional information on overload tolerance, risk acceptance, and corrective operating actions, which are left for future work [27,28,40].

Installation variables are linked to changes in the in-service option. For the first year, Equation (12) ensures an initial installation, where $z_{k,1}$ indicates installation of option k at Year 1 and $y_{k,1}$ indicates that k is in service at Year 1.

$$z_{k,1} \geq y_{k,1}, \quad \forall k \in \mathcal{K}. \quad (12)$$

The non-decreasing capacity constraint is adopted here as a baseline practical-planning assumption. Its purpose is to represent conventional utility reinforcement logic, in which installed transformer capacity is typically maintained or increased over time as demand grows, thus avoiding frequent replacement cycles driven by temporary fluctuations or short-term economic signals.

This assumption does not imply that downsizing, technology substitution, or parallel-transformer configurations are technically impossible or economically irrelevant. Rather, such alternatives are outside the scope of the present baseline formulation and constitute

relevant extensions for future research, especially in contexts with modular asset strategies or high operational flexibility [17,18,30].

For subsequent years, Equation (13) triggers an installation cost when switching to option k , where $y_{k,t} - y_{k,t-1}$ becomes 1 when option k is selected at year t but was not selected at $t - 1$, thus forcing $z_{k,t} = 1$.

$$z_{k,t} \geq y_{k,t} - y_{k,t-1}, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \setminus \{1\}. \quad (13)$$

To reflect practical planning, downsizing is typically avoided; hence, we enforce non-decreasing installed capacity in Equation (14), where the left-hand side is the installed capacity at year t and the right-hand side is the installed capacity at year $t - 1$.

$$\sum_{k \in \mathcal{K}} S_k y_{k,t} \geq \sum_{k \in \mathcal{K}} S_k y_{k,t-1}, \quad \forall t \in \mathcal{T} \setminus \{1\}. \quad (14)$$

The expected discounted life-cycle cost is minimized as in Equation (15), where $C_{k,t}^{\text{inv}}$ is defined in Equation (4), $C_{k,t}^{\text{fe}}$ in Equation (5), $C_{s,k,t}^{\text{cu}}$ in Equation (9), $y_{k,t}$ selects the in-service option, $z_{k,t}$ triggers investment cost, and π_s is the probability of scenario s . The quadratic term in copper losses arises from $\lambda_{s,k,t}^2$ in Equation (9), yielding a mixed-integer quadratic structure.

$$\min \sum_{t \in \mathcal{T}} \left[\sum_{k \in \mathcal{K}} C_{k,t}^{\text{inv}} z_{k,t} + \sum_{s \in \mathcal{S}} \pi_s \sum_{k \in \mathcal{K}} (C_{k,t}^{\text{fe}} + C_{s,k,t}^{\text{cu}}) y_{k,t} \right]. \quad (15)$$

Algorithm 1 summarizes the proposed procedure, from scenario generation and cost-coefficient computation to model optimization and extraction of replacement timing and right-sizing decisions.

Algorithm 1 Scenario-Based Life-Cycle Cost (LCC) Optimization for Transformer Right-Sizing and Replacement Timing under Demand Uncertainty

- Step 1: System initialization, sets, inputs, and decision variables
 Define planning horizon $\mathcal{T} = \{1, \dots, T\}$, transformer catalog $\mathcal{K}$, and scenario set $\mathcal{S} = \{1, \dots, S\}$.
 Load transformer parameters for each $k \in \mathcal{K}$: nominal rating S_k (kVA), investment cost C_k^{inv} (USD), iron losses P_k^{fe} (W), and copper losses at rated load P_k^{cu} (W).
 Set economic parameters: discount rate r , energy price c_E (USD/kWh), capacity price c_P (USD/kW-year), and loss factor f_{loss} (dimensionless).
 Define binary variables: $y_{k,t} \in \{0, 1\}$ (option k in service at year t) and $z_{k,t} \in \{0, 1\}$ (install/replace with k at year t).
- Step 2: Scenario construction for demand-growth uncertainty
 For each scenario $s \in \mathcal{S}$ define initial demand $D_{s,1}$ (kVA), growth rate g_s (1/year), and probability π_s with $\sum_s \pi_s = 1$.
 Generate annual demand trajectories $D_{s,t}$ using Equation (2) for all $t \in \mathcal{T}$.
 (Optional) If demand is defined by year-by-year projections, replace Equation (2) with the trajectory table.
- Step 3: Discounting and loss-factor configuration
 Compute discount factors DF_t using Equation (3).
 If average and peak demand are available, compute load factor and loss factor using Equations (7) and (8); otherwise set f_{loss} to a representative constant (e.g., 0.45).
- Step 4: Pre-computation of annual discounted cost coefficients
 For all (k, t) compute discounted investment coefficients $C_{k,t}^{\text{inv}}$ using Equation (4).
 For all (k, t) compute discounted iron-loss coefficients $C_{k,t}^{\text{fe}}$ using Equation (5).
 For all (s, k, t) compute loading ratios $\lambda_{s,k,t}$ using Equation (6).
 For all (s, k, t) compute discounted copper-loss coefficients $C_{s,k,t}^{\text{cu}}$ using Equation (9).
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Algorithm 1 *Cont.*

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- Step 5: Model assembly: constraints
 Enforce single option per year: $\sum_{k \in \mathcal{K}} y_{k,t} = 1$ (Equation (10)).
 Enforce adequacy under all scenarios: $D_{s,t} \leq \sum_{k \in \mathcal{K}} S_k y_{k,t}$ for all (s, t) (Equation (11)).
 Link installation and service variables: $z_{k,1} \geq y_{k,1}$ (Equation (12)) and $z_{k,t} \geq y_{k,t} - y_{k,t-1}$ for $t \geq 2$ (Equation (13)).
 (Optional, baseline assumption) Enforce non-decreasing installed capacity over time (Equation (14)).
- Step 6: Model assembly: objective function (expected discounted LCC)
 Construct the expected LCC objective: discounted investment + expected (iron + copper) losses using Equation (15), i.e.,

$$\sum_t \sum_k C_{k,t}^{\text{inv}} z_{k,t} + \sum_t \sum_s \pi_s \sum_k \left(C_{k,t}^{\text{fe}} + C_{s,k,t}^{\text{cu}} \right) y_{k,t}.$$
- Step 7: Optimization and feasibility checks
 Solve the resulting mixed-integer model (MIQP if Equation (9) yields quadratic terms).
 If infeasible due to extreme scenarios, revise scenario bounds or introduce an overload slack variable with a large penalty (optional extension).
- Step 8: Post-processing: right-sizing and replacement timing
 Extract optimal in-service option each year: $k_t^* = \arg \max_{k \in \mathcal{K}} y_{k,t}$.
 Identify replacement years: $\mathcal{T}^{\text{rep}} = \{t \geq 2 : k_t^* \neq k_{t-1}^*\}$.
 Compute scenario utilization trajectories $\lambda_{s,k_t^*,t}$ via Equation (6) and report expected LCC, capacity path, and replacement timing indicators.
- Step 9: Sensitivity analysis (strongly recommended)
 Repeat Steps 2–8 under variations of $(r, c_E, c_P, f_{\text{loss}})$, upper-demand bounds, and growth families $\{g_s\}$ to assess the sensitivity of the selected initial rating and replacement timing.
-

3. Results

This section reports the numerical results obtained with the proposed scenario-based optimization framework for transformer right-sizing under demand–growth uncertainty. The base case considers a 15-year planning horizon and a set of nine scenarios obtained from the combinations $D_1 \in \{45, 50, 55\}$ kVA and $g \in \{3\%, 4\%, 5\%\}$. The associated scenario probabilities are $[0.0625, 0.125, 0.0625, 0.125, 0.25, 0.125, 0.0625, 0.125, 0.0625]$, so that the central scenario corresponds to $D_1 = 50$ kVA and $g = 4\%$.

The following subsections examine the base-case result from four complementary perspectives: demand adequacy, loading behavior, discounted cost composition, and decision sensitivity with respect to planning conditions.

3.1. Scenario Characterization and Demand Envelope

Figure 1 shows the uncertainty envelope of apparent power demand together with the optimal transformer capacity path. At the beginning of the horizon, the scenario set spans from 45 to 55 kVA, with an expected demand of 50 kVA. By Year 15, the demand envelope widens to approximately 68.1–108.9 kVA, while the expected demand reaches about 87 kVA. Therefore, the total spread between the lowest and highest demand trajectories increases from 10 kVA at Year 1 to more than 40 kVA at Year 15.

The optimization model selects a transformer rating of 112.5 kVA from Year 1 and keeps it unchanged throughout the 15-year horizon. Hence, the optimal policy does not include any intermediate replacement. This result is numerically consistent with the adequacy constraint: the 100 kVA option becomes insufficient in the upper-end scenarios near the end of the horizon, whereas 112.5 kVA is the smallest commercial capacity that remains feasible for all scenarios and all years. Larger capacities, such as 150 kVA and above, are feasible but are not selected by the model.

This result indicates that the Year-1 sizing decision is effectively governed by the upper boundary of the demand envelope rather than by the expected trajectory alone. Because the selected transformer must remain feasible for all scenarios and all years, the optimization is driven by the highest-demand trajectory near the end of the horizon. Therefore, Figure 1 should be interpreted not only as a visualization of demand uncertainty but also as a graphical representation of the conservative adequacy logic embedded in the model.

Figure 1 shows that the proposed method converges to a static, uncertainty-aware initial sizing decision, with the selected capacity remaining above the full demand envelope throughout the study period; the minimum margin occurs under the upper-end scenario in the final years.

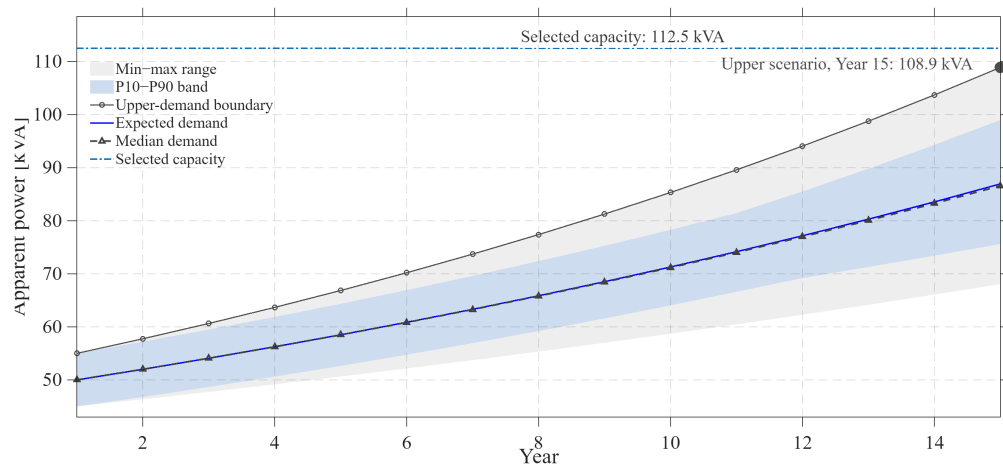


Figure 1. Demand uncertainty envelope and optimal transformer capacity path over the planning horizon.

3.2. Loading-Risk Behavior Under the Selected Policy

Figure 2 presents the evolution of the loading ratio under the selected transformer policy. Since the chosen rating is 112.5 kVA for all years, the loading ratio evolves only as a function of demand growth. At Year 1, the expected loading is approximately 0.44 p.u., while the scenario range is about 0.40–0.49 p.u. At Year 15, the expected loading rises to approximately 0.77 p.u., whereas the upper-end scenario reaches about 0.97 p.u.

These values indicate that the selected transformer remains below the 1.0 p.u. threshold over the entire horizon, even in the most demanding case. At the same time, the loading ratio is well above the very low utilization region during most of the horizon, which indicates that the solution is not excessively oversized. In particular, the expected loading remains between approximately 0.44 and 0.77 p.u., and the median loading follows a very similar trajectory.

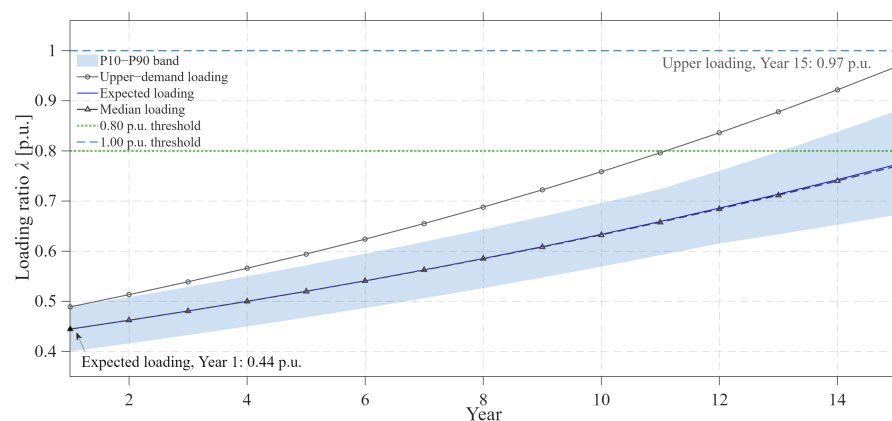


Figure 2. Loading-risk evolution under the selected transformer policy.

From a technical standpoint, the loading trajectories indicate that the selected transformer operates with a narrow but acceptable adequacy margin in the upper-demand scenario while preserving relatively high utilization under expected conditions. This is relevant because it shows that the selected unit is not merely a high-margin oversized choice; rather, it balances feasibility and utilization over the planning horizon.

Figure 2 quantifies the operating margin of the selected transformer, showing that the adopted rating avoids overload while maintaining a relatively high utilization level as demand grows.

3.3. Annual Discounted Cost Composition

Figure 3 decomposes the annual discounted cost into three components: iron-loss cost, copper-loss cost, and investment cost. The expected demand trajectory is superimposed on the secondary axis to directly relate economic behavior to load growth.

The results show that the investment cost is concentrated in the first year of the horizon, due to the initial installation of the selected 112.5 kVA transformer. Since the optimal solution does not include replacement events, no additional investment peaks appear in subsequent years. Therefore, once the initial installation is completed, the total discounted cost is entirely driven by operating losses.

Among these components, the copper-loss cost responds more strongly to demand growth than the iron-loss cost, consistent with the quadratic dependence of copper losses on the loading ratio. In contrast, iron losses remain comparatively stable because they depend mainly on the transformer's energization state and its rated design. As a result, the relative contribution of copper-loss cost becomes progressively more significant as demand increases over the horizon.

Although expected demand rises over time, the annual discounted costs do not necessarily increase monotonically in absolute terms due to discounting. Nevertheless, Figure 3 shows that the economic burden gradually shifts from a CAPEX-dominated first year to a loss-dominated operating regime in the remaining years. However, the annual cost profile alone does not fully explain why a staged reinforcement strategy is not selected. For that reason, Figure 4 complements the cost decomposition with two comparative economic views of replacement timing.

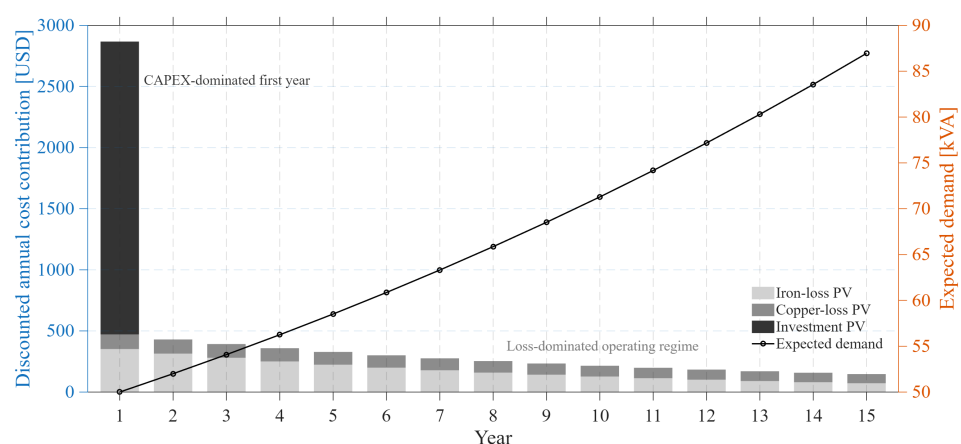


Figure 3. Annual discounted cost composition and expected demand under the selected policy.

Figure 4a presents the original break-even-style comparison between maintaining the current rating and upgrading to a higher one at alternative candidate years. This view is useful for illustrating the economic intuition of replacement timing under the adopted discounted cost structure.

Figure 4b complements that interpretation with a direct comparison between two capacity paths that are especially relevant for the base case: (i) immediate installation of the selected 112.5 kVA transformer from Year 1, and (ii) delayed reinforcement, in which a 100 kVA unit is initially maintained and the upgrade to 112.5 kVA is deferred to a candidate year. By including both the expected and upper-demand trajectories, this second panel makes explicit the trade-off between delaying investment and preserving feasibility under the most demanding scenarios.

Taken together, Figure 4a,b show that, under the adopted scenario set and economic assumptions, delayed upgrades are economically dominated by the initial installation of the selected transformer rating. Although postponing reinforcement may defer capital expenditure, the associated increase in operating losses and the reduced feasibility margin under the upper-demand trajectory prevent the delayed strategy from outperforming the immediate-installation alternative in discounted life-cycle cost terms.

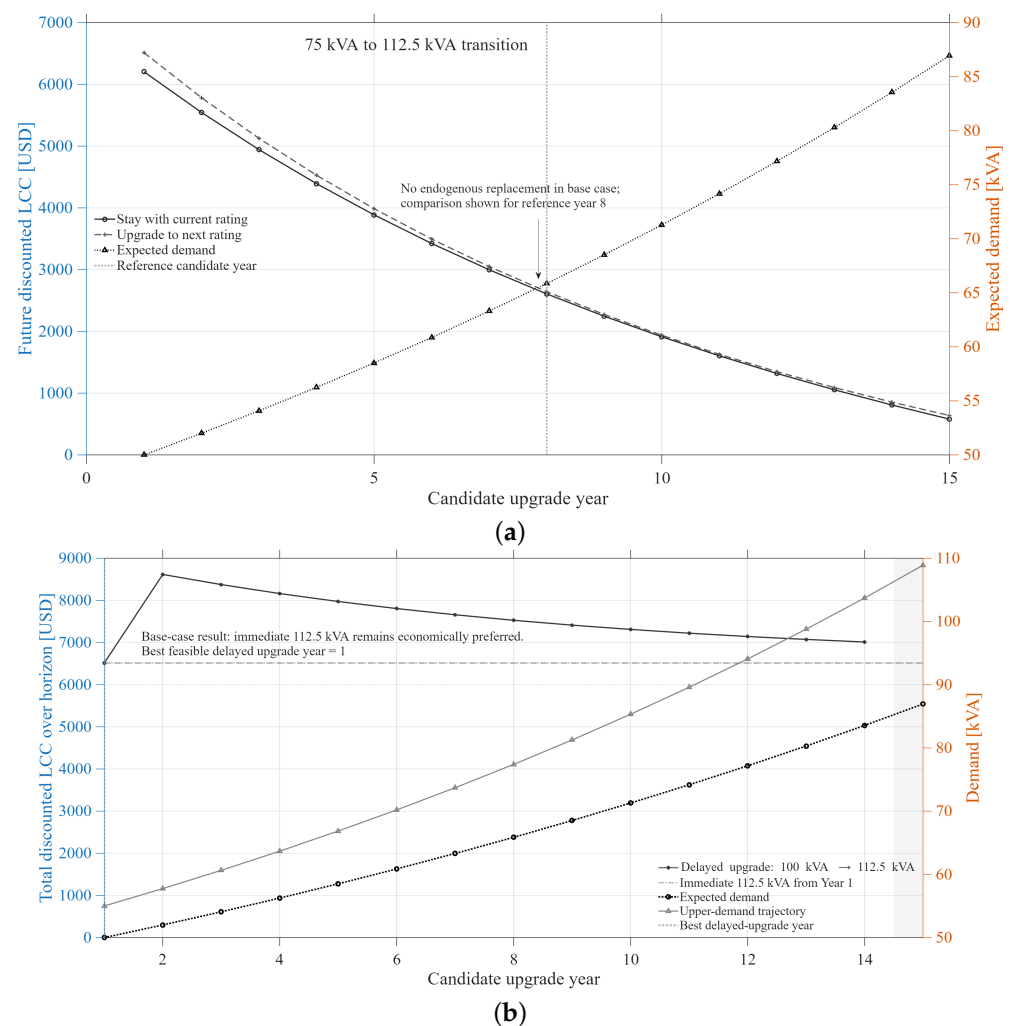


Figure 4. Economic interpretation of replacement timing under the base-case assumptions. (a) provides a break-even-style comparison for candidate replacement years, while (b) compares the immediate-installation solution with a delayed upgrade strategy relevant to the base case. The grey shaded region highlights the late candidate-upgrade years, where delayed reinforcement becomes increasingly less attractive under the base-case demand trajectories.

Therefore, the economic preference for the 112.5 kVA transformer does not arise from minimizing technical losses alone. Instead, it emerges from the joint minimization of discounted capital expenditure, no-load losses, and load losses under the full-scenario adequacy requirement. In this sense, Figures 3 and 4a,b should be read together: Figure 3

explains the evolution of annual economic burden, Figure 4a illustrates the timing logic of replacement, and Figure 4b shows that the immediate 112.5 kVA solution remains preferable over the delayed 100-to-112.5 kVA alternative in the base case. This also explains why larger transformers, although technically feasible, are not economically preferred in the analyzed case.

3.4. Decision-Map Sensitivity to Planning Conditions

Figure 5 extends the analysis by mapping the optimal Year-1 transformer rating as a function of the mean initial demand and the mean annual growth rate. The color scale indicates the selected transformer size in Year 1, while the contour labels indicate the first replacement year, if any.

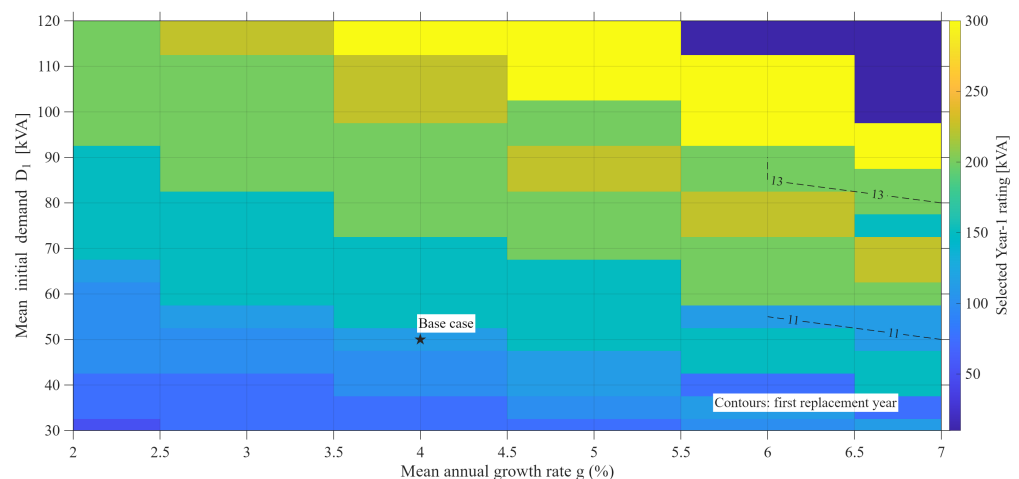


Figure 5. Decision map showing the selected transformer rating in Year 1 and first replacement-year contours as functions of mean initial demand and growth rate.

Figure 5 shows a clear monotonic pattern. In lower-initial-demand and lower-growth regions, the optimal Year-1 rating remains in the lower portion of the catalog, and the replacement contours shift toward later years or disappear entirely. As both the mean initial demand and the growth rate increase, the selected Year-1 rating increases in discrete steps, and the replacement contours shift toward earlier years. Thus, the decision surface is structured into regions rather than varying continuously, consistent with the discrete nature of commercial transformer ratings.

For the base-case region of this study, corresponding approximately to mean initial demands around 50 kVA and mean growth around 4%, the map confirms the detailed optimization result: the preferred initial choice lies in the 112.5 kVA region, and no replacement is activated within the 15-year horizon. This places the base case near the transition between moderate and high loading-growth conditions but still within a region where a one-time initial sizing decision is sufficient.

The numerical results of the base case can be summarized as follows. First, the nine-scenario demand set evolves from an initial range of 45–55 kVA to a final range of approximately 68.1–108.9 kVA. Second, the optimization selects a 112.5 kVA transformer from Year 1 and keeps that rating unchanged over all 15 years. Third, the corresponding expected loading ratio increases from about 0.44 p.u. at the beginning of the horizon to about 0.77 p.u. at Year 15, while the upper-end loading remains below 1.0 p.u. Fourth, the discounted annual cost profile is characterized by a single initial investment and a subsequent operating-cost regime dominated by losses, with an increasing contribution of copper-loss cost as demand grows. Finally, the sensitivity map confirms that the selected 112.5 kVA initial rating is consistent with the broader decision landscape across the considered range of demand–growth conditions.

Beyond confirming the base-case solution, Figure 5 reveals decision boundaries in the (D_1, g) space. These boundaries indicate the combinations of initial demand and annual growth rate for which the economically preferred Year-1 rating changes, and they also identify the regions in which endogenous replacement begins to appear within the 15-year horizon. Therefore, the figure should be interpreted not only as a sensitivity map but also as a threshold map of the planning problem.

From a planning perspective, the practical value of this map lies in showing whether the base case is located far from or close to a decision boundary, since near-boundary cases are more sensitive to revised forecasts and updated economic assumptions.

3.5. Sensitivity Analysis of the Optimal Policy with Respect to Economic Parameters

To evaluate the stability of the policy obtained in the base case, a univariate sensitivity analysis was performed on the model's main economic parameters: the discount rate r , the energy price c_E , the capacity price c_P , and the loss factor f_{loss} . In all cases, the analysis was performed by varying one parameter at a time while keeping the others at their base values, corresponding to $r = 12\%$, $c_E = 0.13$ USD/kWh, $c_P = 60$ USD/kW-year, and $f_{loss} = 0.45$. Table 2 summarizes the analyzed values and reports, for each case, the optimal capacity selected in Year 1, the first year of replacement, and the expected discounted life-cycle cost. In the table, the abbreviation NR indicates that no replacement is triggered within the 15-year planning horizon.

Table 2. Sensitivity of the optimal policy to key economic parameters.

Parameter	Value	Optimal Year-1 Rating (kVA)	First Replacement Year	Expected Discounted LCC (USD)	Change vs. Base Case (%)
Discount rate, r					
8%	0.08	112.5	NR	7754.97	+19.07
10%	0.10	112.5	NR	7078.70	+8.68
12%	0.12	112.5	NR	6513.19	0.00
14%	0.14	112.5	NR	6035.90	−7.33
16%	0.16	112.5	NR	5629.47	−13.57
Energy price, c_E (USD/kWh)					
0.0910	70% of base	112.5	NR	5363.23	−17.66
0.1105	85% of base	112.5	NR	5938.21	−8.83
0.1300	100% of base	112.5	NR	6513.19	0.00
0.1495	115% of base	112.5	NR	7088.17	+8.83
0.1690	130% of base	112.5	NR	7663.14	+17.66
Capacity price, c_P (USD/kW-year)					
42.0	70% of base	112.5	NR	6427.85	−1.31
51.0	85% of base	112.5	NR	6470.52	−0.66
60.0	100% of base	112.5	NR	6513.19	0.00
69.0	115% of base	112.5	NR	6555.86	+0.66
78.0	130% of base	112.5	NR	6598.53	+1.31
Loss factor, f_{loss}					
0.35		112.5	NR	6228.44	−4.37
0.40		112.5	NR	6370.81	−2.19
0.45		112.5	NR	6513.19	0.00
0.50		112.5	NR	6655.56	+2.19
0.55		112.5	NR	6797.94	+4.37

The results show that, within the ranges considered, the structure of the optimal policy does not change: in all evaluated cases, the model maintains the selection of a 112.5 kVA transformer in Year 1 and does not trigger replacements during the study horizon. Consequently, the main effect of the economic variations analyzed is not reflected in the capacity trajectory but rather in the magnitude of the discounted life-cycle cost. In particular, the greatest sensitivity is observed with respect to the discount rate and the energy price, while the influence of the capacity price and the loss factor is comparatively smaller in the case analyzed.

4. Discussion

The results indicate that, for the base-case assumptions adopted in this study, the economically preferred decision is not a staggered sequence of replacements but a single initial sizing action. This outcome should not be interpreted as a universal property of transformer planning; rather, it emerges from the specific combination of a conservative adequacy criterion, a discrete commercial catalog, and the economic coefficients used in the case study. In addition, the economic interpretations provided in Figure 4a,b, together with the sensitivity results summarized in Table 2, reinforce that the base-case policy is internally consistent within the modeled planning framework. Under these assumptions, the replacement problem effectively collapses into the selection of a sufficiently feasible and economically attractive initial capacity.

From an economic perspective, this result can be explained by the balance among three components: initial investment, no-load losses, and load losses. A lower capacity, such as 100 kVA, reduces the initial investment but becomes infeasible in the upper-demand scenarios near the end of the horizon. In contrast, capacities above 112.5 kVA increase capital expenditure and no-load losses without producing a sufficient reduction in expected copper-loss cost to compensate for that additional burden. This trade-off is consistent with the comparisons shown in Figure 4a,b, particularly with the direct base-case comparison between immediate installation of 112.5 kVA and delayed reinforcement from 100 kVA. Consequently, the model identifies 112.5 kVA as the smallest commercial rating that simultaneously preserves technical adequacy under the full demand envelope and minimizes discounted life-cycle cost in the base case.

The results also indicate that the proposed formulation does not favor extreme over-sizing. Although the selected policy is conservative in terms of feasibility, the loading profile remains within technically reasonable values throughout the planning horizon. This is relevant because it shows that the optimization does not enforce reliability simply through excessive margin; instead, it identifies a technically tight yet feasible solution that maintains relatively high asset utilization under expected demand conditions. In this sense, the methodology provides a more consistent alternative to deterministic margin-based sizing, since the final choice results from an explicit trade-off among uncertainty, losses, and investment costs. Moreover, the sensitivity results reported in Table 2 suggest that this interpretation remains unchanged across the tested economic variations, even though the total discounted cost does vary.

Another important aspect is that the reported solution depends on the adopted uncertainty structure and on the conservative feasibility requirement imposed across all scenarios. Therefore, the no-replacement outcome should not be interpreted as evidence that replacement timing is irrelevant but rather as a consequence of the scenario set, the adequacy-for-all-scenarios criterion, and the discrete transformer catalog used in the case study. In the current configuration, 112.5 kVA is the first commercial rating that remains feasible above 100 kVA, which strongly influences the resulting policy. This interpretation is consistent

both with the threshold structure observed in Figure 5 and with the fact that, within the economic ranges summarized in Table 2, the selected capacity path does not change.

At the same time, the economic preference for installing 112.5 kVA in Year 1 should be interpreted with caution. This result is conditional on the adopted economic coefficients, the absence of explicit thermal–operational flexibility, and the use of a single-policy planning formulation. Although the sensitivity analysis in Table 2 indicates that the selected capacity path remains unchanged within the tested ranges, the associated discounted life-cycle cost varies appreciably, especially with the discount rate and the energy price. Under alternative assumptions, such as controlled overload risk, dynamic transformer rating, staged recourse decisions, or different capital-cost conditions beyond those analyzed here, a smaller initial transformer followed by later reinforcement could become economically attractive.

From an asset-planning perspective, this result has several practical implications. First, it shows that right-sizing and replacement timing do not necessarily appear as multiple replacement events; in some planning contexts, the main value of the model lies in justifying a single initial capacity decision on economic and technical grounds. Second, it highlights that the discretization of the commercial transformer catalog directly affects the optimal policy, as wide rating steps may cause relatively small demand changes to push the solution toward the next available commercial size. Third, it confirms that explicitly incorporating demand uncertainty changes the traditional sizing logic based only on expected demand or deterministic engineering margins. In addition, Figure 5 and Table 2 show that the practical interpretation of the result should consider both the position of the base case within the broader decision map and its sensitivity to plausible economic variations.

In this sense, the present no-replacement outcome should be read as a base-case economic optimum rather than as evidence that phased reinforcement is generally dominated. The practical value of the framework lies precisely in identifying when replacement timing ceases to be an endogenous decision and when it reappears under changed demand growth or economic conditions. In the present manuscript, this point is supported by the complementary evidence provided by Figure 4a,b, the threshold structure of Figure 5, and the economic sensitivity summarized in Table 2.

Limitations and Future Work

This study has several limitations that should be considered when interpreting the base-case result. First, demand is represented through annual aggregate trajectories and a finite scenario set with predefined probabilities. This choice is suitable for medium-term strategic planning, but it does not capture intrayear variability, seasonal loading patterns, abrupt structural changes, or correlated uncertainty drivers that may affect transformer loading in practice. Therefore, the no-replacement outcome obtained in the base case should be interpreted as conditional on the adopted demand-envelope representation rather than as a universally transferable conclusion.

Second, the model adopts a conservative adequacy criterion by requiring feasibility for all scenarios and all years, together with a non-decreasing installed-capacity assumption. These modeling choices are useful for constructing a transparent and computationally tractable planning baseline, but they may favor earlier or larger initial sizing decisions than alternative formulations based on probabilistic adequacy, controlled overload risk, recourse decisions, or staged reinforcement policies. In particular, under planning settings that explicitly allow for temporary overload management or corrective actions, a smaller initial transformer followed by a later upgrade could become economically attractive.

Third, the present formulation monetizes iron and copper losses through annualized cost coefficients, but it does not explicitly internalize transformer thermal dynamics,

hot-spot temperature evolution, accelerated insulation aging, or loss-of-life accumulation. As a result, the proposed framework should be interpreted as a strategic techno-economic planning model rather than as a detailed thermo-operational asset-life model. Likewise, the use of a representative loss factor improves tractability when detailed load data are unavailable, but it should be recalibrated whenever feeder-specific hourly or AMI-based measurements are available.

Fourth, the economic analysis is based on fixed coefficients for discount rate, energy price, capacity price, and investment cost. Although this is standard in baseline planning studies, these parameters may vary significantly over a 15-year horizon due to regulatory changes, market conditions, financing structures, or utility-specific procurement practices. Consequently, the economic preference for the selected 112.5 kVA transformer should be understood as a base-case optimum under the adopted coefficients, not as a parameter-independent recommendation.

Finally, the applicability of the framework depends on the availability of a calibrated transformer catalog and representative local planning data. The current paper demonstrates the method in a structured case-study setting, but additional validation with utility data would strengthen its practical transferability and would allow for a more realistic calibration of scenario bounds, probability assignments, and economic coefficients.

Future work should therefore extend the framework in four directions: (i) richer uncertainty representations, including probabilistic or multistage formulations; (ii) explicit thermal-aging and transformer life-loss models based on sub-hourly loading and ambient temperature data; (iii) integration of flexibility resources and operational mitigation measures, such as dynamic transformer rating, controlled EV charging, storage, or distributed generation; and (iv) validation with real utility datasets to assess how the preferred capacity path changes under utility-specific technical, economic, and regulatory conditions.

5. Conclusions

This paper presented a scenario-based optimization framework for evaluating transformer right-sizing and replacement timing under demand-growth uncertainty. The formulation jointly considers discrete commercial transformer ratings, discounted investment cost, monetized iron and copper losses, and a finite scenario set over a 15-year planning horizon. For the case study analyzed, based on nine combinations of initial demand and annual growth rate, the optimal solution selects a 112.5 kVA transformer in Year 1 and maintains that capacity throughout the horizon.

A relevant result is that no replacement event is triggered in the optimal policy under the adopted base-case assumptions. This indicates that, for the scenario set and economic coefficients considered, the preferred decision is not a phased expansion strategy but a single initial sizing action. The economic interpretation developed in Figure 4a,b supports this result by showing that delaying reinforcement does not outperform the immediate installation of 112.5 kVA in discounted life-cycle cost terms. In particular, the 100 kVA option becomes infeasible in the most demanding scenarios toward the end of the horizon, while alternatives above 112.5 kVA are economically penalized by their higher investment cost and greater contribution to no-load losses.

From a technical standpoint, the selected transformer maintains acceptable utilization margins throughout the planning horizon, with expected loading increasing from approximately 0.44 p.u. to 0.77 p.u., while the upper-demand scenario remains below 1.0 p.u. Economically, the optimal policy is characterized by a single initial investment followed by an operating regime increasingly influenced by loss costs, particularly copper losses as demand grows. In addition, the sensitivity results summarized in Table 2 indicate that, within the tested economic ranges, the selected capacity path remains unchanged

even though the discounted life-cycle cost varies, especially with the discount rate and the energy price.

In summary, the main contribution of this work is to show that transformer right-sizing and replacement assessment should be addressed jointly under uncertainty rather than solely through deterministic margins. In the analyzed case, the framework provides a quantitative justification for selecting 112.5 kVA as the preferred initial rating from both an economic and a technical-feasibility perspective. More broadly, the proposed approach offers a transparent planning baseline for distribution asset management and can be extended in future work toward probabilistic adequacy criteria, explicit thermal-aging models, and coordinated flexibility resources.

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

Abbreviations

The following abbreviations are used in this manuscript:

AMI	Advanced metering infrastructure
BESS	Battery energy storage system
CAPEX	Capital expenditure
DER	Distributed energy resources
DR	Demand response
DT	Distribution transformer
DTR	Dynamic transformer rating
EV	Electric vehicle
LCC	Life-cycle cost
MILP	Mixed-integer linear programming
MIQP	Mixed-integer quadratic programming
p.u.	Per unit
PV	Photovoltaic
TCO	Total cost of ownership

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