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Trigger rules optimization for adaptable investment in distribution substation capacity under uncertainty: Untapping the value of flexibility

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ABSTRACT

The rise of intermittent renewable generation and the electrification of demand are causing grid congestion and connection delays in some countries, a trend expected to expand as the energy transition progresses. At the same time, distribution system operators face high uncertainty in forecasting peak loads due to the unpredictable adoption pace of technologies such as electric vehicles, distributed generation, and industrial electrification. This paper presents a stochastic optimization model to determine the optimal timing of substation capacity investments combined with flexibility solutions under uncertainty. The model builds on the real options framework and employs triggers as decision rules (e.g., investing in a transformer once peak load exceeds a threshold), resulting in adaptable strategies, in which future investment decisions are contingent on unfolding information rather than fixed planning schedules. The model optimizes these triggers and reveals strong synergies with flexibility solutions, achieving 15.1% expected savings and 64.9% expected reduction in reserved flexibility compared to the traditional approach in our case study. Adaptable strategies may lead to anticipatory investment in some scenarios and deferral in others compared to the traditional planning approach, striking a balance between faster connections and cost-efficiency. This adaptability is particularly valuable given the current high-uncertainty context. The case study shows that these benefits grow as available flexibility increases. From a regulatory standpoint, these trigger rules can support conditional approval of anticipatory grid investments, contingent on confirmation of the investment need (e.g., peak load exceeding a set threshold), thereby limiting the risk of such investments becoming stranded assets.

1. Introduction

The electricity distribution network faces significant challenges in operation and planning due to the increase in intermittent renewable generation and the penetration of distributed energy resources. Different European countries already experienced congestion in distribution networks [1], countries like Germany are already noticing this effect, and are increasingly facing congestion due to generation peaks in wind farms. At the same time, the Netherlands is also experiencing congestion due to peaks from renewable generation and increasing loads from data centers. Norway is experiencing increasing penetration of electric vehicles (EVs) and associated congestion due to EV charging. The United Kingdom is facing congestion mainly due to renewable generation and EVs. While congestion in distribution grids in some other countries is not yet a relevant issue, it is likely to increase as the penetration of renewables and distributed energy resources (DERs) spreads across countries, compromising distribution networks' hosting capacity and delaying grid connections or limiting the operation of existing resources.

The pace of adoption of new technologies (i.e., the penetration of EVs and other DERs) is uncertain, as network planners such as the UK National Grid ESO have noted. Their annual report includes projections for peak electricity demand in the United Kingdom up to 2050 [2]. Among the scenarios projected by UK National Grid ESO, there are different paths to achieving net-zero objectives, and even the possibility of not reaching them by 2050. Likewise, Moberg [3] shows the wide range of forecasts for electricity demand in Sweden by 2045, with predictions from various institutions ranging from a minimum increase of 16% [4]

Abbreviations: ACER, European Union Agency for the cooperation of energy regulators; ADN, Active distribution network; CAPEX, Capital expenditure; CEER, Council of European Energy Regulators; DER, Distributed energy resource; DG, Distributed generation; DNP, Distribution network planning; DSO, Distribution system operator; EV, electric vehicle; GBM, Geometric Brownian motion; LDC, Load duration curve; NRA, National regulatory agency; OPEX, operational Expenditure; VoLL, Value of lost load; WACC, Weighted average cost of capital.

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Notation

Sets

b	forecasted base scenarios without noise $\{1, \ldots, B\}$
h	hours in the year $\{1, \ldots, 8760\}$
s	forecasted scenarios with added noise $\{1, \ldots, S\}$
t, a	years in the planning period $\{1, \ldots, T\}$

Parameters

∇P_t	maximum expected increment of peak load in year t for years between $t-1$ and t + FLT across long-term base scenarios. Expressed as a percentage.
CL	Initial substation capacity limit. (MW).
$ENS^0_{s,t}$	energy not served without any intervention to solve grid problems at scenario s and year t (MWh).
$ENS^F_{s,t}$	energy not served if flexibility is reserved at scenario s and year t (MWh).
$ENS^G_{s,t}$	energy not served if grid is reinforced at scenario s and year t (MWh).
$F^{Av}_{s,t}$	maximum available flexibility in scenario s and year t (MW).
$F^{act}_{s,t}$	total amount of flexibility to reserve in scenario s and year t (MWh).[1]
$F^{act}_{s,t,h}$	amount of flexibility to reserve in scenario s, year t and hour h (MWh).[1]
$F^{res}_{s,t}$	amount of flexible energy to reserve in scenario s and year t (MWh).[1]
$FC^{res}_{s,t}$	flexibility capacity to reserve for scenario s and year t (MW).
FLT	lead time for flexibility. (years).
$\mathrm{FR}^{\mathrm{Cost}}$	flexibility reserve cost (€/MW/h).
$\mathrm{FU}^{\mathrm{Cost}}$	flexibility utilization cost (€/MWh).
G^{CAPEX}	Annuity of the grid reinforcement, considering a set of equal payments, that account for the capital cost and the depreciation of the grid asset during its useful life. The interest rate considered is the WACC (€).
GLT	lead time for grid reinforcement. (years).
GRC	increase in capacity limit by grid reinforcement (MW).
LDC^0_h	Value of the load duration curve in initial year (t = 0) and hour h (MW).
$\mathrm{LDC}_{s,t,h}$	load duration curve for scenario s year t and hour h (MW).
$LDC^{max}_{s,t,h}$	load duration curve projected based on $P^{max}_{s,t}$ (MW).
M	a large numerical value with the purpose of relaxing the constraint.
P_0	peak load observed in initial year (t = 0). Initial data point for all the forecasted scenarios (MW).
$P_{b,t}$	peak load in base scenario b and year t (MW).
$P_{s,t}$	actual peak load in scenario s and year t (MW).
$P^{max}_{s,t}$	maximum expected peak load for year t and scenario s (MW).
Pr_s	probability of scenario s.
$T_{s,t,h}$	takes value of 1 if $LDC^{max}_{s,t,h}$ surpasses the capacity limit, and 0 otherwise.
$T^{res}_{s,t}$	hours of flexibility to reserve in scenario s and year t (h).
$VoLL$	value of lost load (€/MWh).
WACC	weighted average cost of capital.
ϵ	a small numerical value with the purpose of avoiding strict inequalities when formulating constraints.

Variables

$\delta_{s,t}$	1 if no intervention is made, 0 if either grid is reinforced or flexibility is reserved for scenario s and year t.
$ens_{s,t}$	energy not served (i.e., excess of load) in scenario s and year t (MWh)
f^1	1 if flexibility is reserved at year 1 for all scenarios s, 0 otherwise.
$\mathrm{f}^{\mathrm{act}}_{\mathrm{s,t,h}}$	flexibility to activate in scenario s and year t. (MWh)
$g_{s,t}$	1 if grid reinforcement is in service at year t and scenario s, 0 otherwise.
i^1	1 if decided to invest in grid reinforcement at year 1 for all scenarios s,0 otherwise.
$i_{s,t}$	1 decided to invest in grid reinforcement at year t and scenario s, 0 otherwise.
$r^F_{s,t}$	1 if flexibility is reserved for scenario s and year t, 0 otherwise.
tr^F	trigger level for reserving flexibility (MW).
tr^G	trigger level for investment in grid reinforcement (MW).
$tr^{G-act}_{s,t}$	1 if peak load in scenario s' and year (t-1) reaches or surpasses the grid reinforcement trigger; 0 otherwise.

[1] This flexibility is reserved, and then activated, only if there is a flexibility trigger activation in the corresponding scenario and year, according to the methodology described in section 3.

to a maximum increase of 125% [5].

In this context, it is critical to anticipate the need to connect new grid users (generators, consumers, storage) while ensuring cost efficiency, reliability, and minimizing electricity losses. Therefore, this situation presents a trade-off between some of the mentioned objectives, e.g., anticipating the need to connect new users and avoiding an over-dimensioned network that would increase tariffs for network users. The high uncertainty DSOs face intensifies this trade-off, and regulatory agencies are looking for ways to ensure high service levels, avoid delays in new connections, and maintain low tariffs.

Some regulatory agencies, such as the Spanish National Commission on Markets and Competition (CNMC), are considering regulating anticipatory investments [4], as proposed by the European Commission in the Grid Action Plan [5]. In March 2024, the Council of European Energy Regulators (CEER) published a report analyzing this issue [6]. The report highlights that the critical factor in approving infrastructure developments is the certainty about the investment's value and necessity. Furthermore, CEER provides recommendations for implementing anticipatory investments, suggesting that National Regulatory Authorities (NRAs) could allow projects to progress through permit-granting and other preconstruction activities as much as possible, even before regulatory approval is given. The latter approval is conditional and would be issued only once the need for the investment is confirmed.

This view aligns with existing regulatory practices observed among certain NRAs, which, as noted in [6], have granted conditional approvals for investments whose necessity has yet to be confirmed. Such conditional approvals can shorten the lead time for network adaptation once the requirement for reinforcement is confirmed. Establishing clear criteria for approving specific network investments enhances regulatory certainty, a highly desirable attribute in the regulation of critical infrastructure. This practice requires a definition of the conditions that confirm the need for investment. However, traditional planning techniques based on discounted cash flow define the year for a future investment (e.g., invest in a feeder in year 3 of the planning period). In contrast, adaptable strategies define decision rules to confirm the need for investment (e.g., invest in a feeder when its peak load reaches 30 MW). Waiting for a signal to confirm the investment need aligns with the view expressed by [6] for implementing anticipatory investments. Thus, an NRA may approve an investment from a DSO based on the decision rule defined in the investment plan, for example, the investment in a feeder is approved when the peak load reaches 30 MW. This conditional approval expedites reinforcement, as the DSO no longer has to wait for approval once the need is confirmed, enabling faster connections.

However, implementing conditional approval is not straightforward because distribution network planning[2] (DNP) is a complex problem, and most current planning methodologies do not result in decision rules. This is where the real options framework becomes particularly valuable, as it provides structured decision rules that define the conditions under which an investment should be deemed necessary. This approach facilitates the implementation of conditional approvals in the regulatory framework of distribution networks.

In addition, other conditions suggest a potential benefit to using the real options approach. The real options framework is suggested when an investment opportunity is partially or completely irreversible, there is uncertainty about future outcomes, and there is some leeway in the timing of the investment decision [7]. Under these conditions, the real options framework is known for its potential to increase economic efficiency, which is exactly what distribution network planners face today. First, there is high uncertainty about future demand and peak load evolution, as already motivated at the beginning of this section. Second, grid reinforcements of the distribution network are considered irreversible investments. Third, peak network utilization (both injections and withdrawals) can be shaved using flexibility solutions, giving planners some leeway in the timing of the investment, allowing DSOs to maintain high service levels without committing to the irreversible investment until the investment need is confirmed. Therefore, there is a synergy between the real options framework and flexibility solutions, providing an opportunity to increase economic efficiency when planning investments in the distribution network. The trigger-based decision-making concept has been proposed for congestion management in network operations, where DSOs face uncertainty and flexibility solutions are available [8].

The main objective of this study is to develop a methodology for determining the optimal timing of investments in substation capacity, combined with the use of flexibility solutions under uncertainty, using trigger-based decision rules within a real options framework.

This methodology is tested in a case study that examines a substation in a distribution network and compares two strategies to manage congestion: reinforcing the grid by adding new infrastructure or procuring flexibility from connected users. The methodology evaluates and optimizes these options under uncertainty about future load growth, considering costs and implementation timelines. The initial cost of flexibility considered in the case study is based on average values observed in UK flexibility markets [9], and the initial available flexibility capacity considered is 7% of the peak load at the beginning of the planning period, in line with estimates reported in previous studies (6%) [10] and real DSO experience (8%) [11]. Given prior experience showing that the availability and cost of flexibility can vary greatly by location and may be affected by the maturity of the local flexibility market [9], a sensitivity analysis of both flexibility availability and cost is conducted to assess whether the results remain robust under different assumptions.

Results show increased efficiency in network planning by implementing the proposed real options methodology compared to a traditional fixed-decision approach. Moreover, the proposed approach results in a more efficient use of flexibility; the savings it provides remain relevant even with high-priced flexibility and increase as more flexibility becomes available.

1.1. The complexity of the DNP problem and the proposed simplifications

Planning investments in the distribution network presents different challenges, including a computational burden due to its complexity. Defining the location, sizing, and timing of distribution network investments over a planning period requires simplifications. Moreover, considering a more active DSO role beyond the traditional fit-and-forget approach, including active distribution network (ADN) solutions such as flexibility (e.g., demand response) and network reconfiguration, increases the problem complexity [12]. Even more, considering the uncertainty currently faced by DSOs adds another layer of complexity. Researchers propose various simplifications, leading to different research lines.

Some technical simplifications have been proposed [13] (e.g., linear approximations, typical seasonal profiles, etc.). Other simplifications regarding the optimization method include using metaheuristics (e.g., tabu search and particle swarm optimization). [14] presents a literature review assessing the performance of the different metaheuristics used to solve the DNP problem. These metaheuristics reduce the computational burden of finding a solution, even allowing the solution of non-linear problems. Still, these complex algorithms do not guarantee optimality, and DSOs may hesitate to use them in favor of simpler approaches [13].

Some simplifications rely on planning approaches (e.g., the single-stage and pseudo-dynamic approaches), which we will discuss in detail in Section 2.1. The single-stage approach does not meet the DSO needs, as regulators often require DSOs to present multi-year plans; however, it may serve as an initial step in the planning exercise to identify investment candidates as input for the multi-stage approach [15]. The real options approach results in actionable, adaptable plans by defining decision rules. In contrast, other multi-stage approaches (i.e., dynamic, pseudo-dynamic, and stochastic approaches) that do not consider the real options framework result in a distribution network plan with fixed decisions (e.g., investing in a new transformer in the 2nd year of the planning period).

Considering the real options approach adds a layer of complexity to the DNP problem, and its effective implementation requires addressing two key aspects. First, the approach should enable adaptable planning by defining decision rules. Second, the considered uncertainty should not be modeled with Geometric Brownian Motion (GBM) distributions, a practice inherited from the financial domain, which does not adequately capture the uncertainties that DSOs face. Further discussion is provided in the state-of-the-art review in Section 2.

1.2. Summary of the research gap

Existing literature on real options for distribution networks does not provide an optimization framework for assessing investment in the distribution network that properly implements the real options methodology. There are three critical elements to achieve this:

- Defining decision rules that allow adaptable investment strategies.
- Considered multi-scenario uncertainty in line with current DSO planning practices.
- Proposing a multi-scenario optimization framework, either exact mathematical optimization or using *meta*-heuristics.

The first two elements are essential for a rigorous implementation of the real options thinking to assessing investments in the distribution

[2] Distribution network planning is the process of determining required network upgrades over a planning period to ensure reliable, safe, and cost-efficient power delivery to end users.

network. The third element is crucial to ensuring the adoption of the methodology, as planning approaches typically rely either on mathematical optimization models to guarantee optimal solutions or on metaheuristics to at least achieve near-optimal solutions in complex problems.

This study proposes a specific trigger definition and formulates a stochastic optimization model that fills a gap in the current literature by allowing a multi-stage multi-scenario stochastic optimization model based on the real options framework, in which:

- Planning decisions adapt to unfolding information.
- Decision rules (triggers) are mathematically optimized considering multiple scenarios for long-term uncertainty (in line with current DSO practices).
- Flexibility solutions are explicitly integrated with traditional grid investments.

As a result, the paper provides a practical framework for assessing investment timing in distribution networks, overcoming the limitations of previous works. A detailed discussion of the research gap is described in Section 2.3.

1.3. Adopted approach and contributions

The first objective of this study is to develop a stochastic optimization model for assessing investments in substation capacity (i.e., assuming a single node capacity-limited network model) in combination with the use of explicit flexibility[3] solutions (i.e., the possibility of contracting flexibility with connected users) under uncertainty based on a real options approach that results in adaptable planning strategies.

The second objective of this study is to demonstrate that the proposed formulation can deliver substantial benefits in the current decarbonization context characterized by high uncertainty about future demand growth. These benefits include increased efficiency in network planning and the definition of triggers that enable conditional approval of anticipatory investments, as suggested by European regulators [6].

While previous studies have proposed a real options approach to assess investment timing and the use of flexibility solutions in the distribution network, this paper makes some key contributions, which can be summarized as follows:

- Bringing attention to two key considerations for a rigorous implementation of the real options thinking in assessing investments in the distribution network: (i) the need for proper uncertainty representation, and (ii) the need to define decision rules, so the resulting plans are actionable. These elements are often overlooked, yet they are essential for ensuring a realistic and practical implementation of the real options approach.
- An optimization model based on real options for assessing investments in substation capacity, combined with an explicit consideration of flexibility solutions. The proposed model uses triggers as decision variables, resulting in adaptable strategies and actionable plans. The trigger variables determine whether to reinforce the grid and whether to reserve flexibility based on the evolution of peak load across scenarios.
- Results show that adaptable strategies, combined with flexibility solutions, increase economic efficiency by 10% to 16% in most scenarios compared to the traditional fixed-decisions approach. These savings may not always come from increased expected investment deferral, but also from more efficient use of flexibility, with a 64.9% reduction in flexibility reserve and 21% reduction in flexibility activation in our base case study.
- Results show that adaptable strategies do not always defer investment compared to the traditional approach; instead, they may anticipate investments if certain conditions are met during the planning period, while deferring investments if these conditions are not met.
- Furthermore, the proposed trigger variables not only allow for a mathematical optimization formulation but also result in intuitive decision rules that can be easily implemented by DSOs. These practical decision rules may serve as a basis for regulators to conditionally approve anticipatory investments. Different European regulatory agencies have suggested conditional approval for anticipatory investments [6], and the proposed trigger definition and methodology facilitate the implementation of this recommendation.

This paper is organized as follows. Section 2 reviews previous studies that propose using real options to assess investments in the distribution network and discusses key considerations for implementing this approach, while identifying the literature gap this work addresses. Section 3 presents the proposed methodology and its mathematical optimization formulation for assessing investment timing and the use of flexibility solutions in the distribution network. Section 4 describes the case study to test the proposed methodology. Section 5 discusses the case study's results, highlighting the advantages of the proposed methodology and the synergies between the real options approach and flexibility solutions. Finally, Section 7 summarizes the article's conclusions and outlines future research lines.

2. State of the art: Real options for assessing investments in the distribution network

Integrating the real options framework into the distribution network problem (DNP) is not straightforward due to the DNP's inherent complexity. Section 2.1 presents an overview of the planning approaches used in DNP, highlighting the benefit of the real options approach. Section 2.2 reviews how previous research addressed the two key aspects for implementing the real options approach for assessing investments in the distribution network. Finally, Section 2.3 presents the research gap that this study addresses.

2.1. The planning approach in DNP

Next, we give a general overview of the planning approaches in DNP, single-stage and multi-stage, respectively, based on previous literature reviews, and mention some particular studies. This overview is not exhaustive by any means; its purpose is to summarize the simplifications made across the different approaches and some of their main limitations. This discussion motivates the importance of integrating a real options approach in DNP.

2.1.1. The single-stage approach

The single-stage distribution planning approach aims to define the location and sizing of investments in the distribution network, only considering one planning stage (i.e., one period). Considering a single planning stage simplifies the DNP problem, reducing the computational burden. There are many published studies presenting methodologies for single-stage DNP, as shown by different reviews [12,14], some of them including ADN features, such as the provision of ancillary services by customers connected to EV charging stations [16] and by residential and small industry customers with DERs [17]. The inclusion of multiple planning alternatives is complex. For instance, an optimization framework for allocating distributed generation, battery energy storage systems, and EV charging stations within distribution networks is presented in [18]. Even under a single-stage approach in a medium-sized network, the consideration of multiple planning alternatives along with multiple

[3] Flexibility is defined as “the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system” [44].

objectives, such as loss minimization, voltage stability, and cost reduction, requires metaheuristics. Few studies combine ADN features with a large-scale network, and these studies require metaheuristics, such as tabu search [19] and particle swarm [20], to reduce the computational burden. The lack of studies of large-scale networks that include ADN features and the use of metaheuristics highlight the complexity of the DNP problem, even when considering a single-stage approach.

The single-stage planning approach is incomplete, as regulators often require DSOs to present multi-period plans. Still, this approach can serve as an initial step to identify investment candidates, as input for a multi-stage analysis, as proposed by [15].

2.1.2. The multi-stage approach

The multi-stage distribution planning approach aims to define the timing, location, and sizing of network investments during the planning period. We may distinguish between the pseudo-dynamic and the dynamic approach [21].

The pseudo-dynamic or stage-by-stage approach executes the single-stage approach multiple times. Not considering all the time effects and consequences of interdependencies between stages when executing the optimization algorithm, often relying on backward or forward iterations to include the pseudo-dynamic aspect [22,23]. This approach does not guarantee the optimality of the results, but it reduces the complexity compared to the dynamic approach.

The dynamic approach considers multiple stages in the optimization process, producing more valuable results than the pseudo-dynamic approach because it contemplates all interdependencies between stages. Additionally, this approach may acknowledge future uncertainties, resulting in a multi-stage, multi-scenario approach, but this increases complexity. Then, it is interesting to discuss the different simplifications proposed. The first simplification is the scenario reduction into a single scenario. Since the distribution network is a critical infrastructure, scenario reduction typically only considers the worst-case scenario (i.e., a robust optimization approach), resulting in conservative plans as noted by [24].

On the other hand, the stochastic approach allows multiple scenarios to be considered simultaneously during the optimization. However, most studies using the stochastic approach ignore the managerial flexibility to adjust future investment decisions contingent on unfolding information during the planning period, as highlighted by [25]. For example, it may be reasonable that the investments in the distribution network will vary based on the actual evolution of peak load. Still, these plans propose locked or fixed future decisions (e.g., invest in a new transformer in the 2nd year and then invest in a new feeder in the 5th year). Some researchers [26,27] noticed this circumstance and proposed a stochastic optimization approach recognizing the managerial ability to react to future information by allowing different investment decisions at each scenario and period. Nevertheless, as explained by the authors in [26], these plans are only valid for present-time investment decisions because they lack a decision rule to define the necessary conditions to make future investment decisions and do not result in actionable plans for future investment decisions. This lack of a decision rule it necessary to repeat the assessment methodology at each stage and hampers the conditional approval of investments.

All these multi-stage approaches are obstacles to the approval of conditional anticipatory investments because they either result in fixed decisions or cannot define an actionable plan (i.e., a plan with decision rules) that specifies future investment decisions contingent on unfolding information. The real options framework results in adaptable strategies that overcome this barrier, resulting in actionable plans that adapt to future conditions. Moreover, adaptable strategies based on real options synergize with flexibility solutions, increasing the potential savings for the system [10,28].

2.2. The real options framework: Key aspects for its implementation

Various studies have identified the potential of implementing the real options framework to assess investments in the distribution network, particularly when considering flexibility solutions. However, implementing the real options framework is not straightforward, and there are two key considerations for a successful implementation.

- First, the real options approach should consider adaptable strategies.
- Second, the uncertainty representation should fit the DSO context.

Next, we discuss these two considerations and review whether previous studies have addressed them.

2.2.1. Adaptable strategies

The real options approach allows the decision maker to postpone investment decisions until the uncertainty is at least partially resolved [29]. Therefore, this approach should result in adaptable strategies. The methodology should define the decision rules with the specific conditions that result in future decisions during the planning period, as highlighted by [30]. Some DNP studies do not adequately address this consideration.

Authors in [15,31] propose a risk-based optimization approach for analyzing investment in the distribution network considering distributed generation (DG) and conventional investment alternatives, and show that DG investment is a valuable alternative under uncertainty. Similarly, [32] studied investment decisions in the distribution network under uncertainty, considering DG as an alternative to traditional investment alternatives. This study concludes that DG can potentially increase efficiency and technical performance in the distribution network. [26] noticed that [15,31] methodology results in a plan with fixed decisions, and not adaptable strategies, missing the first key characteristic of the real options approach, and the same argument is valid for the methodology presented in [32].

2.2.2. Uncertainty consideration

Considering multiple scenarios when representing uncertainty in DNP is particularly relevant, as it aligns with current industry practice for planning investments in the distribution network. For example, in the UK, public network plans by UKPN [33] reflect the requirements set by Ofgem, under which load-related investments must be justified against a range of plausible scenarios [34].

An assumption inherited from options analysis in the financial world is to model uncertainty as a Geometric Brownian Motion (GBM). GBM-based approaches, which assume lognormal project value distributions, are unlikely to capture the nature of energy projects [25]. A scenario-based approach to represent uncertainties, such as peak load evolution, offers a more practical methodology. However, most previous studies that have implemented a real options approach in DNP modeled uncertainty as a GBM.

Authors in [26] and [35] propose a methodology for assessing investments in the distribution network, considering DG investments and their relocation. They conclude that DG increases adaptability to uncertain scenarios and recommend combining DG with traditional investment. A real options approach to assess traditional investments and network reconfiguration in the distribution network under uncertainty is proposed in [36], concluding that the potential efficiency of the ADN solution (i.e., network reconfiguration) increases with the real options approach, consistent with previous studies. [37] presents a methodology to evaluate traditional investments in the distribution network under uncertainty using a real options approach. [33] proposes a method for assessing DG investments in the distribution network as a temporary solution, allowing the deferring of traditional investments using a real options approach. More recently, [34] proposed a real options approach for planning distribution networks that considers investments in DSO-owned DERs, such as energy storage systems and diesel generators, under supply chain risks as a source of uncertainty. The study concludes that the real options approach effectively handles supply chain risks, enhancing overall efficiency. Another recent study [38] proposed a real options approach for planning investments in the distribution network, considering flexibility solutions as a planning alternative and uncertainty in load growth and investment costs. They conclude that the real options approach increased the value of flexibility solutions in distribution network planning.

All these studies [15,26,31–38] represent uncertainty using a GBM distribution to use the Black-Scholes method for option valuation or a binomial lattice approximation of the GBM proposed by Cox, Ross, and Rubinstein [39]. As discussed, authors in [25] noted that this assumption represents a barrier to the practical implementation of the real options approach for assessing investments in the distribution network.

Some authors have also proposed using real options to assess investment in the electricity transmission network [40]. This work proposes implementing the real options approach using decision trees to leverage the long permitting processes for transmission network expansion (up to 10 years). They propose reevaluating the investment decision after the permitting process is complete. The decision framework is a two-stage decision tree, suitable for this specific purpose and designed to evaluate the investment decision in two stages: one before and one after permitting is obtained. However, this approach is not suitable for assessing investments in the distribution network using a multi-stage, multi-scenario approach. Similarly, authors in [41] propose a two-stage decision tree to evaluate the flexibility embedded in transmission expansion planning by evaluating line capacity utilization across the planning period to adjust the investment decision in light of unfolding information. However, authors in [41] recognize the limitations of the approach due to its simplification of the long-term uncertainty being embedded in two-stage decision trees. The decision tree is not a suitable approach for considering demand-growth uncertainty in distribution network planning, as the number of nodes would grow exponentially.

A real options approach for assessing distribution network investments that incorporates demand response as a flexibility solution is presented in [10]. The load growth from the most likely scenario is applied annually to each individual scenario to derive peak-demand projections. Investment decisions are triggered when projected demand in each scenario exceeds the network asset capacity, including available flexibility. Although the study in [10] addresses two key aspects of the real options approach, it relies on a deterministic decision rule rather than optimizing it. This deterministic assessment, along with the absence of an optimization process, limits the methodology's potential for guaranteeing efficient decisions.

2.3. Research gap and adopted approach

Table 1 shows the characteristics of the studies proposing the use of real options to assess investments in the distribution network, along with the gap this study addresses. In the literature, no previous optimization model has properly implemented real options thinking to assess investments in the distribution network. While [15,31], and [32] fail to define decision rules that result in adaptable strategies. [26,33–38] assume long-term uncertainty representation in line with assumptions coming from the financial world that may be valid for valuing stock price variations, but do not fit the DSO context as explained in Section 2.2. Finally, [10] properly implements the real options framework but does not develop an optimization model; instead, it relies on deterministic assumptions to calculate a trigger rule without an optimization process.

Table 1
Characteristics of methodologies applying the real options framework to the DNP problem, considering flexibility solutions as an alternative to grid reinforcement.

References	Adaptable strategies	Considered uncertainty fitting the DSO context	Optimization model considering multiple scenarios
[15,31,32]	No	No	Yes
[26,33–38]	Yes	No	Yes
[10]	Yes	Yes	No
This study	Yes	Yes	Yes

This work addresses a gap in the current literature by proposing an optimization model that properly implements the real options framework to assess the timing of investment in substation capacity. Flexibility solutions, considered alongside traditional grid reinforcement, are treated as a core element of the decision-making process. The methodology introduces a simple, practical definition of trigger rules, which are optimized through a multi-stage, multi-scenario stochastic optimization model to minimize expected cost. The result of the proposed approach is an adaptable investment strategy with investment decisions contingent upon unfolding information during the planning period. The combination of adaptable strategies and flexibility solutions creates a synergy that unlocks additional value from flexibility resources. Uncertainty is modeled through multiple scenarios following standard industry practices. Our study is aligned methodologically with [26,33–38] because it proposes an optimization model to assess investments in the distribution network, and it is aligned conceptually with [10] by proposing a proper implementation of the real options tailored to the problem. To the best of our knowledge, no previous study has proposed an optimization model that properly implements the real options framework to assess investments in the distribution network.

3. Methodology

This paper presents a stochastic optimization model for assessing the timing of grid reinforcement and the use of flexibility solutions to mitigate potential future congestion in a distribution substation, using a real options approach that results in adaptable strategies in which planning decisions are contingent on unfolding information during the planning period.

The methodology considers an investment in substation capacity and a DSO forecast of peak load based on multiple scenarios, each assigned a probability of occurrence. The methodology in this paper assumes a simple network model (i.e., a single node and a capacity limit), suited to the study's purpose. This methodology may serve as a basis for future extensions to consider the real options approach in more complex network models, such as multi-node network models with AC or DC power flows. However, incorporating these features would significantly increase the computational burden of the problem, as the trigger optimization would need to be combined with non-linear power flow constraints and higher-dimensional decision spaces (multiple candidate solutions). In Section 7, we recommend a sequential approach for considering large-scale networks as a future research line.

A load duration curve is projected for each scenario and year of the planning horizon. If the peak load of these scenarios exceeds the current capacity limit, it may lead to congestion and service interruptions (i.e., energy not served). To address these potential grid issues, the DSO has identified two alternatives.

First, a traditional reinforcement that would increase the substation's capacity limit. This reinforcement solves the potential problems. The lead time for this reinforcement, the investment cost, and the increase in the capacity limit after the reinforcement (e.g., 15 MW of additional capacity) are all inputs for the proposed model. The computed cost of the alternative in this study is a constant annuity that accounts for asset depreciation and the cost of capital over the asset́s useful life. An assumption is that the investment candidate (e.g., the transformer to build) is already identified; this input may come from running a single-stage approach for the most unfavorable expected conditions during the planning period.

As a second planning alternative, there is the possibility of deferring this investment by reserving flexibility, for example, by contracting services from a provider that commits to reducing a certain amount of load within a specific timeframe if the DSO sends an activation signal. The cost of this alternative for the DSO is the sum of the costs for reserving flexibility (€/MW/h) and for activating flexibility (€/MWh). There is also an associated lead time with the flexibility, which defines the time between reserving flexibility and its potential activation.

The objective of the DSO is to find the minimum-cost solution for the planning period while maintaining a high service level. To maintain a high service level, the methodology considers a value of lost load (VoLL), measured in €/MWh, that increases the cost based on the energy not served during the planning period.

The methodology uses a practical decision rule by defining triggers. The level of the triggers defines when to reinforce the grid and when to reserve flexibility for each scenario. A trigger, expressed in MW, represents the load level that, once surpassed, automatically triggers the decision to either reinforce the grid or reserve flexibility. Section 3.2 provides a detailed explanation of this decision-making mechanism. The model results in adaptable strategies in which future decisions are contingent on unfolding information during the planning period. Particular emphasis is placed on the stochastic optimization model that optimizes the level of these triggers (i.e., decision rules).

Fig. 1 summarizes the proposed methodology. The inputs for the optimization model are the forecasted scenarios (forecasts of future peak load, load duration curve (LDC) and probability of each scenario), along with the identified investment alternatives (maximum available flexibility, flexibility lead time, the reinforcement candidate and its lead time), the grid parameters (substatioń s capacity limit) and the economic parameters (value of lost load, weighted average cost of capital, costs for reserving and activating flexibility, and annual cost of the grid reinforcement alternative).

The stochastic optimization model identifies the minimum-cost solution for the planning period by optimizing the trigger levels for flexibility reserve and grid reinforcement. The model's output includes the expected costs associated with grid investment, flexibility, and energy not served, as well as the expected flexibility utilization (in MWh) and the expected energy not served (in MWh).

Next, we provide a detailed description of the methodology.

3.1. Forecasted scenarios & grid parameters

The base scenarios represent the peak load forecasts for the planning period. Fig. 2 presents an example based on National Grid (UK) "Future Energy Scenarios 2023" [2].

3.1.1. Scenario generation & short-term uncertainty (noise)

These base scenarios for peak load represent the long-term uncertainty. Then, we use a Monte Carlo simulation to add noise to these base scenarios, representing the short-term uncertainties, such as renewable production and load variability. The noise is modeled as a normal distribution with a mean of 0 and a standard deviation that can be modeled according to the conditions of the study, as suggested in a previous study [10]. Fig. 3 illustrates one base scenario in blue and three scenarios in grey resulting from adding noise representing short-term uncertainty, using a normal distribution.

After calculating the peak load for each scenario and year, their corresponding load-duration curves are projected.

3.1.2. Load duration curve & the substatioń s capacity limit

The load duration curve provides a graphical representation of the load variations over the year, in this case with hour granularity. The loads ranked in descending order help calculate and visualize the number of hours the analyzed system operates over a certain load level (e.g., the substation's capacity limit).

The load duration curve for a particular scenario and year is a projection that applies the peak loads growth rate (i.e., $P_{s,t}/P_0$) to the load duration curve of the base case (i.e., LDC_h^0), see Fig. 4. This implicitly assumes that the form of the load duration curve remains constant over the planning period; this assumption may be ignored, and the rest of the methodology may be applied without further adjustments. Equation (1) shows the mathematical description of this projection.

$$LDC_{s,t,h} = LDC_h^0 * P_{s,t}/P_0 \forall s,t,h \tag{1}$$

The substation's capacity limit is its thermal limit. If the load in a particular hour h, scenario s, and year t exceeds this limit, it results in not served energy unless flexibility is contracted or the grid is reinforced. The energy not served would be the area of the LDC that is above the capacity limit, the yellow-filled area in Fig. 4.

The use of LDC overlooks chronological time dependencies, which are crucial for accurately modeling batteries as flexible resources or considering demand rebound effects. This limitation is explained in Section 6, along with future research lines to overcome it.

3.2. Decision-making: Relevance of triggers for deciding when to reinforce the grid and when to reserve flexibility

Typically, peak load drives investment decisions in the distribution network, while flexibility solutions enable peak shaving, reducing the need for traditional grid reinforcement. In this methodology, the evolution of peak load triggers future investment decisions. In contrast, present decisions are binary (i.e., invest or not) based on currently available information and forecasted scenarios. For example, the DSO may invest in a new feeder immediately or set a trigger level (e.g., 20 MW) to invest in the future, as peak load evolves. If a trigger is set, the investment decision is made whenever the peak load reaches that threshold.

Similarly, the decision to reserve flexibility today is binary. The decision to reserve flexibility depends on whether the peak load reaches a predefined trigger level (e.g., 18 MW), typically set below the existing capacity limit. This ensures that flexibility is available for activation when the peak load exceeds the substation's capacity. The primary difference between the decision to reserve flexibility and to invest in a grid asset is that the latter is a multi-year commitment. Once the DSO decides to invest, this represents an irreversible decision. While reserving flexibility does not represent a multi-year commitment or irreversible decision, the DSO may choose to reserve flexibility in a particular year and not in the following year of the planning period.

Figs. 5 and 6 illustrate the results of the decision-making approach proposed in this methodology, which defines two triggers. In both figures, the green, black, and blue lines represent forecasted peak-load scenarios, representing long-term uncertainty, while the red dotted line represents the current capacity limit. In Fig. 5, the purple dotted line represents the trigger for reserving flexibility. If the peak load evolves as the black line, the peak load will surpass the flexibility trigger (i.e., the purple line) during year 1; therefore, at the beginning of year 2, the DSO will decide to reserve flexibility, considering a one-year lead time for flexibility reserve, and this reserved flexibility will be available for activation in year 3. Similarly, in Fig. 6, the brown dotted line represents the trigger for grid reinforcement. If the peak load surpasses the grid reinforcement trigger during year 3, the DSO will decide to reinforce the grid at the beginning of year 4. As the lead time considered for the reinforcement is three years, the grid reinforcement will be in service at the beginning of year 7. Notice that, depending on the scenario that unfolds, the peak load surpasses the triggers for flexibility and grid reinforcement at different years in the planning horizon (years 4 and 7 for the blue scenario, and years 6 and 8 for the green scenario). This difference shows that establishing triggers leads to adaptable plans where future decisions are contingent on unfolding information during the planning period.

The flexibility reserve signal is only one component of the decision-making process regarding flexibility reserve. The full process includes

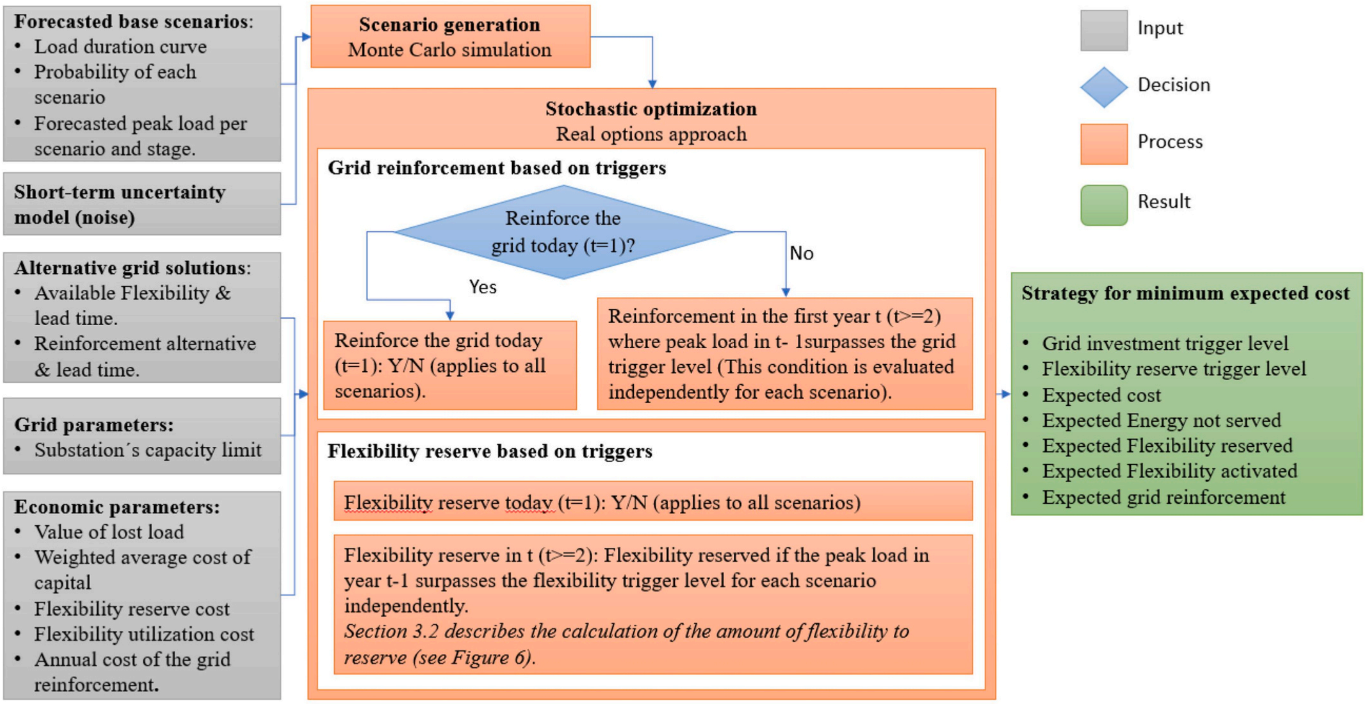

Fig. 1. Methodology summary.

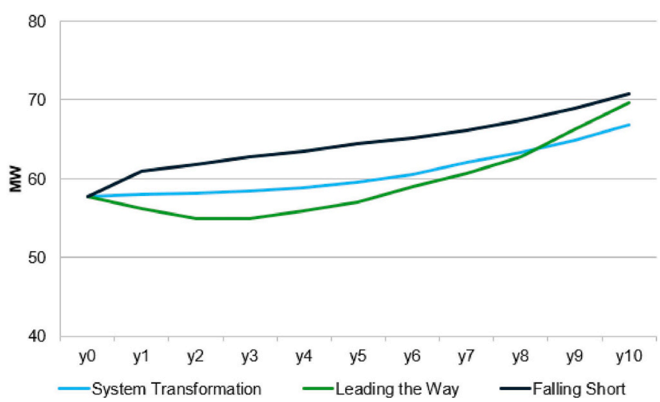

Fig. 2. Base scenarios based on National Grid Future Energy Scenarios 2023. Electricity system peak-demand forecast.

determining the exact amount of flexibility to reserve. This is discussed next.

3.2.1. The amount of flexibility to reserve using a real options approach

This approach proposes a simple and practical rule to define the flexibility to reserve at each scenario and year, based on the real options framework. This proposal establishes a specific rule for its calculation using the most recent available information at the moment of decision-making.

At the beginning of any year t within the planning period, the methodology determines the flexibility to reserve for activation during year $t+FLT$ based on the available information, where FLT represents the flexibility lead time in years. This information includes the base scenarios, which provide the initial forecasts of the peak load at the beginning of the planning period (as shown in Fig. 2), as well as the actual evolution of peak load from the initial year (t = 0) to the most recent observed peak load at year t-1.

Fig. 7 illustrates the decision-making process for reserving flexibility in year t for scenario s.

The first step in Fig. 7 is to determine whether the grid reinforcement is expected to be in service at year $t + FLT$.[4] If it is in service in that year, there is no need to reserve flexibility in t for activation in $t + FLT$, as peak shaving becomes unnecessary once the reinforcement is operational. Otherwise, we proceed to the second step in Fig. 7 to determine whether the peak load in t-1 surpassed the flexibility trigger, as illustrated in Fig. 6. If the peak load in t-1 does not exceed the flexibility trigger, the process terminates, and no flexibility is reserved. Otherwise, we need to calculate the amount of flexibility to reserve based on the available information.

To determine the flexibility to reserve, the next step is to project the peak load for period $t + FLT$. This begins with calculating the maximum expected load growth rate between t-1 and $t + FLT$, denoted as ∇P_t. This rate is derived from base scenarios (i.e., scenarios without noise) as shown in equation (2), see Fig. 8 for an illustrative example.

$$\nabla P_t = max_b\left(\frac{P_{b,t+FLT} - P_{b,t-1}}{P_{b,t-1}}\right)\forall t \geq 1 \tag{2}$$

Next, the calculated growth rate, ∇P_t, is applied to the actual peak load observed in scenario s and year $t-1$, denoted as $P_{s,t-1}$, to estimate the peak load projection for $t + FLT$, as defined in equation (3) and illustrated in Fig. 9. This projection, $P^{max}_{s,t+FLT}$, serves as a ceiling for the expected peak load as it assumes the maximum possible load growth over the period between $t-1$ and $t + FLT$.

$$P^{max}_{s,t+FLT} = P_{s,t-1}(1 + \nabla P_t)\forall s, 1 < t \leq T - FLT \tag{3}$$

The peak load projection at any year t, denoted as $P^{max}_{s,t}$, and the capacity limit, CL, determines the amount of flexibility to be reserved for scenario s and year t, expressed in megawatts, $FC^{res}_{s,t}$. However, this reserved amount cannot exceed the available flexibility, $F^{Av}_{s,t+FLT}$, as enforced by equation (4).

[4] If the decision to reinforce the grid is made at $t+FLT-GLT$ or before, the grid reinforcement is expected to be in service at $t + FLT$.

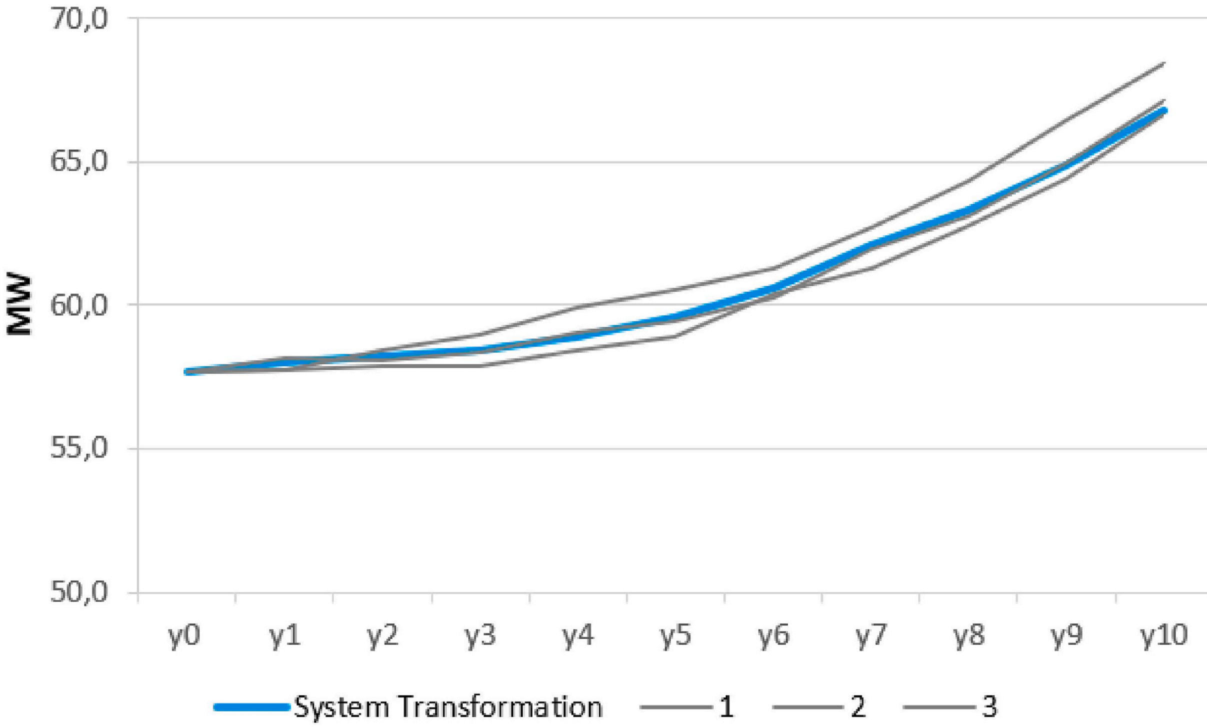

Fig. 3. Illustration of three scenarios resulting from one base scenario and added noise. Electricity system peak-demand forecast.

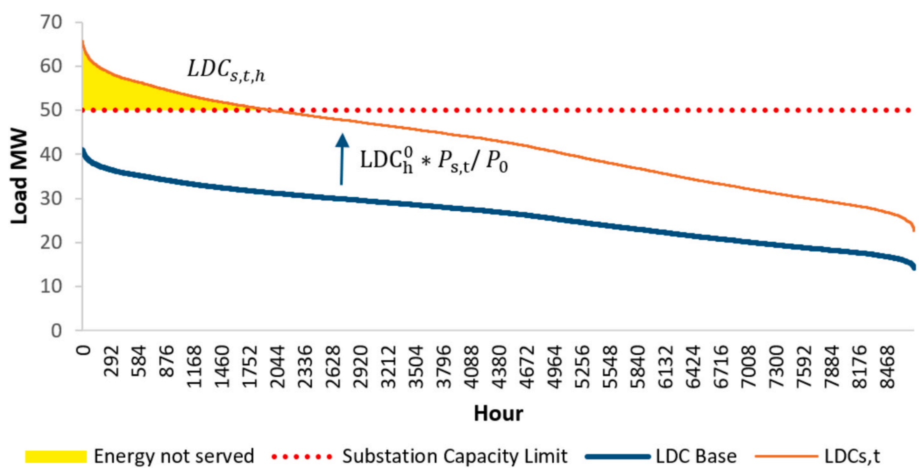

Fig. 4. Illustration of the substatiońs capacity limit, load duration curve, and energy not served with no intervention.

$$FC^{res}_{s,t} = \begin{cases} \min\left(P^{max}_{s,t} - NC, F^{Av}_{s,t}\right) P^{max}_{s,t} - CL, \geq 0 \\ 0 P^{max}_{s,t} - CL < 0 \end{cases} \forall t, s \tag{4}$$

This approach provides a conservative estimate of the required flexibility capacity, as it is based on the maximum expected peak load, ensuring sufficient flexibility is reserved to address potential increases in peak load.

The calculated amount of flexibility, $FC^{res}_{s,t}$, is reserved for the duration in which the projected LDC for scenario s and year t exceeds the capacity limit, $T^{res}_{s,t}$. The maximum expected peak load, denoted as $P^{max}_{s,t}$, is used to project the maximum expected load duration curve, $LDC^{max}_{s,t,h}$, following equation (5). This LDC projection, $LDC^{max}_{s,t,h}$, is used to determine the time for the flexibility reserve, following expressions (6) and (7), according to the aforementioned conservative approach.

$$LDC^{max}_{s,t,h} = \frac{P^{max}_{s,t}}{P_0} * LDC^0_h \forall s, t >= 1 + \mathrm{FLT},\ \mathrm{h} \tag{5}$$

$$T_{s,t,h} = \begin{cases} 1 LDC^{max}_{s,t,h} - CL > 0 \forall s, t >= 1 + FLT, h \\ 0 LDC^{max}_{s,t,h} - CL \leq 0 \forall s, t >= 1 + FLT, h \end{cases} \tag{6}$$

$$T^{res}_{s,t} = \sum_h T_{s,t,h} \forall s, t >= 1 + \mathrm{FLT}, h \tag{7}$$

Then, equation (8) shows the calculation of the flexibility to reserve in $MW{*}h$, $F^{res}_{s,t}$, as the product of the capacity to reserve, $FC^{res}_{s,t}$, and the time to reserve, $T^{res}_{s,t}$.

$$F^{res}_{s,t} = T^{res}_{s,t} * FC^{res}_{s,t} \forall s, t \tag{8}$$

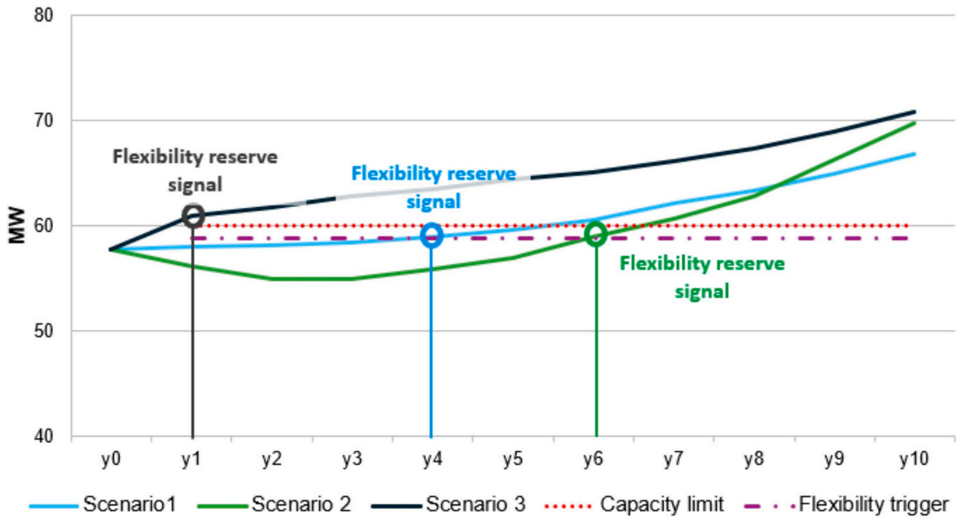

Fig. 5. Proposed decision-making approach based on triggers for flexibility reserve.

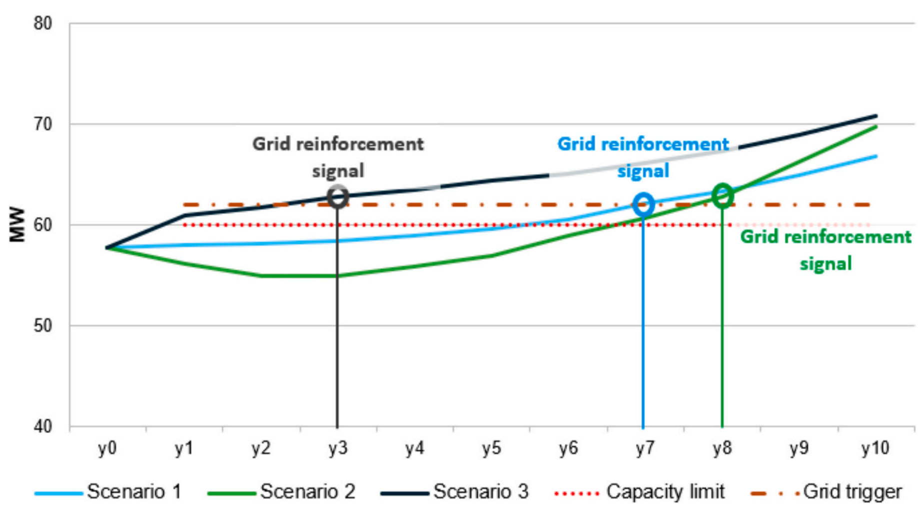

Fig. 6. Proposed decision-making approach based on triggers for grid reinforcement.

Based on the described methodology, this approach for determining the amount of flexibility to reserve enables calculations to be performed before executing the optimization model, across all scenarios and planning years. As a result, the reserved flexibility quantities serve as input parameters to the optimization model. The flexibility trigger is treated as a decision variable in the optimization process, allowing the model to determine whether or not the DSO reserves flexibility at a given year and scenario.

Subsection 3.3 outlines the methodology for calculating the energy not served, considering both the grid investment decision and the decision to reserve flexibility.

3.3. Alternative grid solutions & economic parameters

As mentioned at the beginning of section 3, this methodology assumes that the DSO has identified two alternative solutions to address potential grid problems during the planning period. First, a traditional grid reinforcement (e.g., a transformer or a feeder). Second, the possibility of contracting flexibility from connected users.

The model takes several key inputs: the capacity increase from grid reinforcement, its lead time, the available megawatts (MW) of flexibility, and its lead time. Additionally, the model considers the following economic parameters: the annualized cost of grid reinforcement, the costs associated with reserving and activating flexibility, the weighted average cost of capital, and the value of lost load.

3.3.1. Calculation of the energy not served

Fig. 10 illustrates the methodology for the calculation of the energy not served and the flexibility to activate in scenario s and year t. The capacity limit in year t for scenario s is the sum of the initial substation capacity limit and the reinforcement (if in service) or flexibility (if reserved). The actual load duration curve is then compared with the capacity limit to obtain the energy not served. Formulation details are included in the equations (9)-(13).

Fig. 11 illustrates the calculation of the energy not served for scenario s and year t when no grid reinforcement is in service and flexibility is reserved. The flexibility is reserved during peak hours, and the capacity limit is increased by the flexibility reserved during these peak

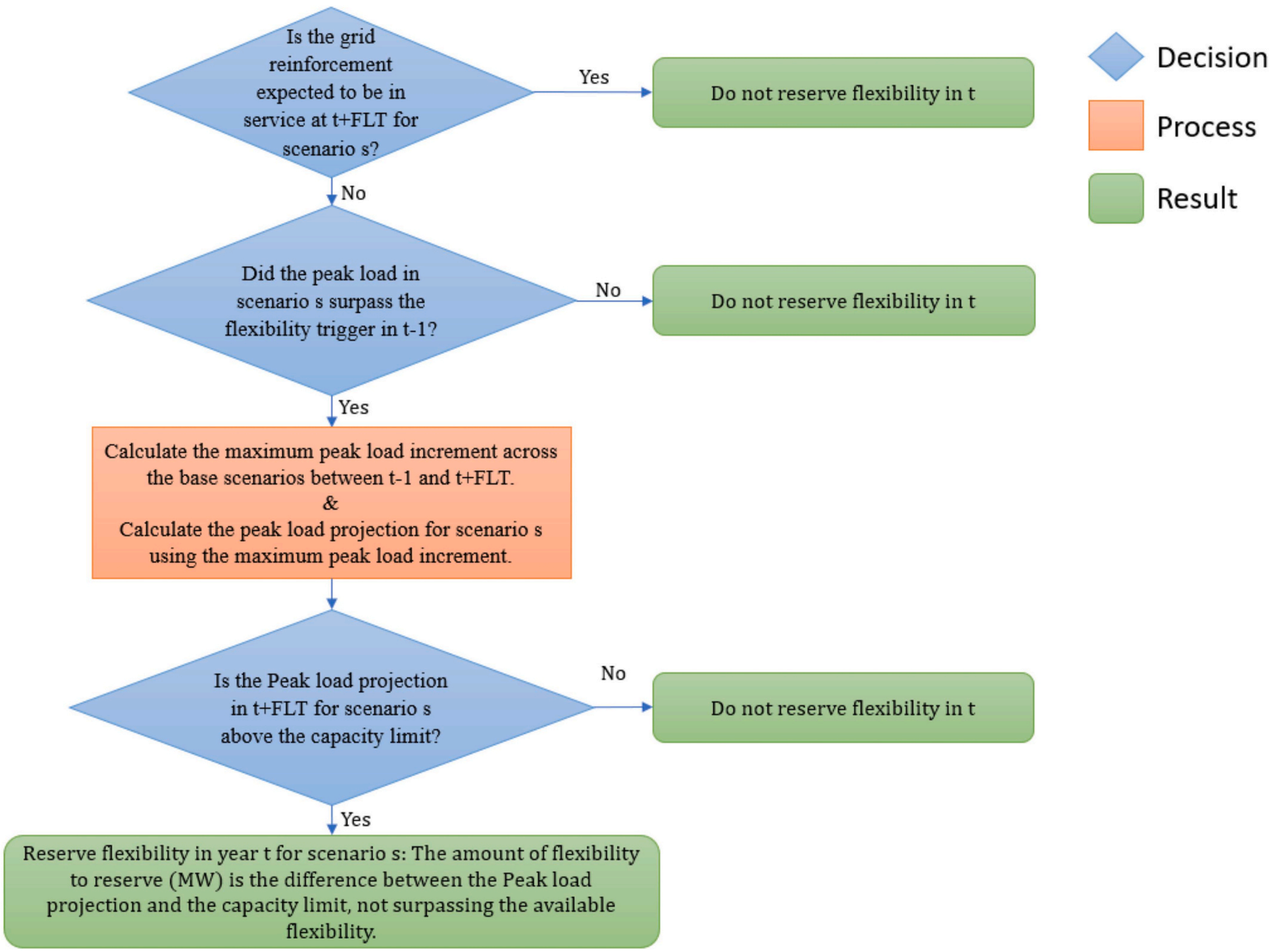

Fig. 7. Decision-making process to reserve flexibility using the real options approach.

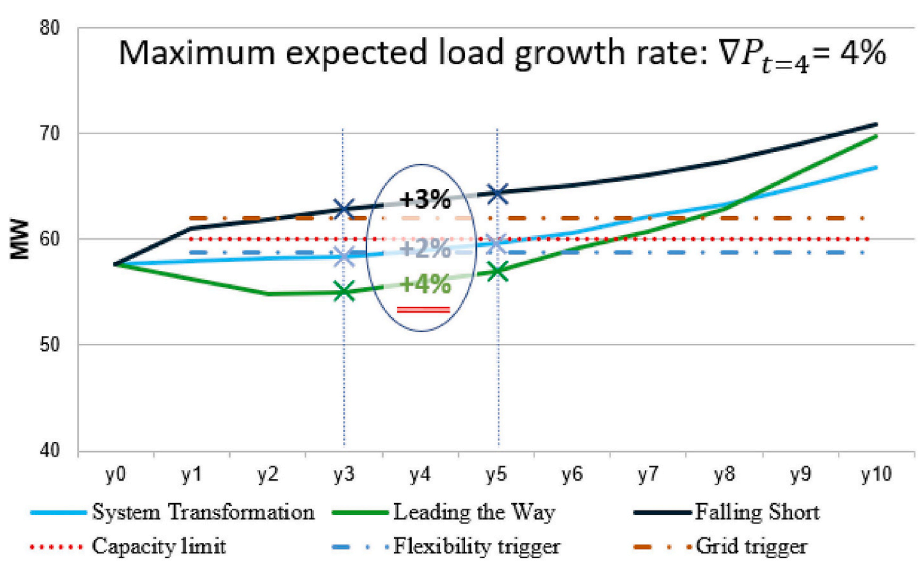

Fig. 8. Illustrative example of maximum expected load growth rate in t = 4, assuming FLT = 1 year.

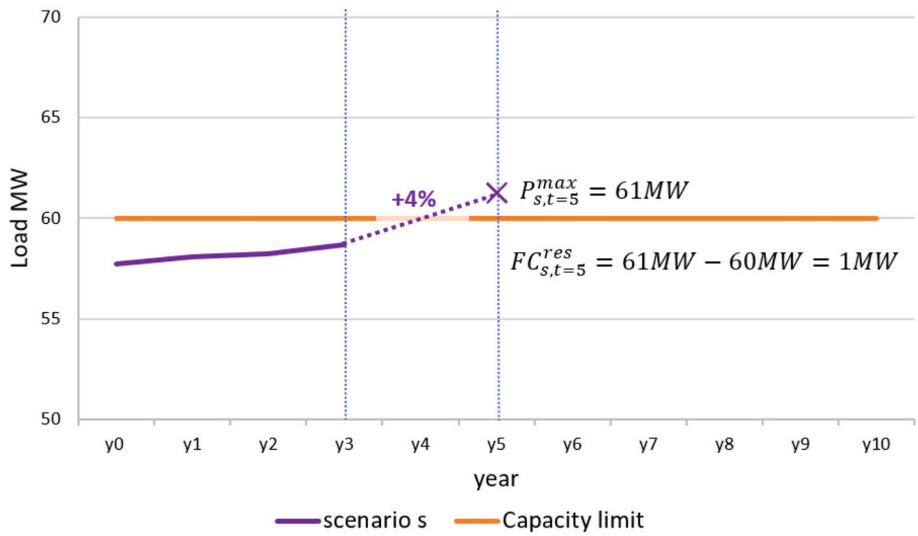

Fig. 9. Illustrative example of peak load projection for t = 5 in scenario s, based on maximum expected load growth between t = 3 and t = 5, and the actual peak load observed in t = 3.

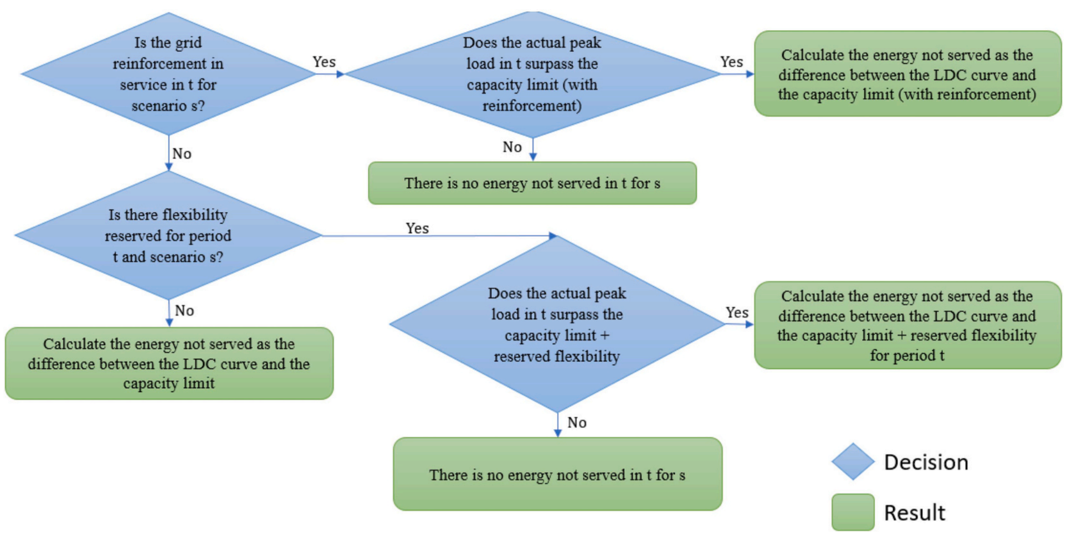

Fig. 10. Calculation of energy not served for scenario s and period t.

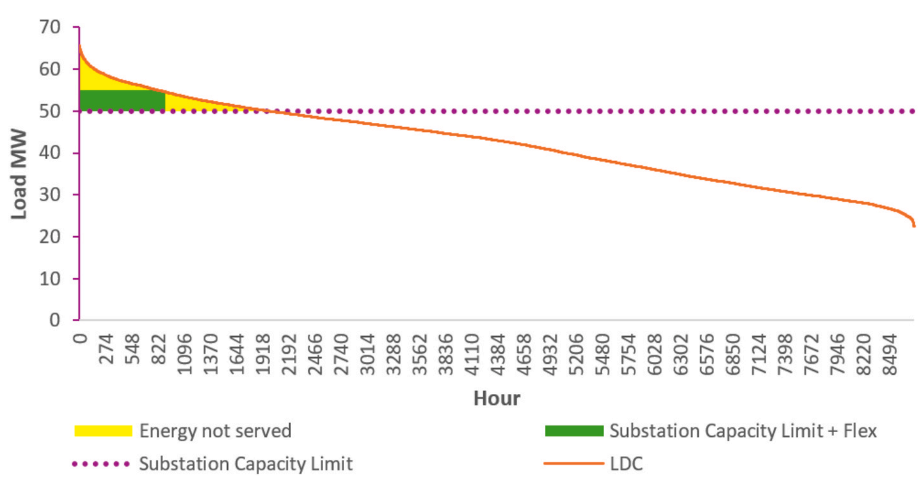

Fig. 11. Illustration of the substationś capacity limit, the load duration curve, and the amount of energy not served if flexibility is reserved.

hours. Therefore, the energy not served (yellow filled area) is reduced, and the reserved flexibility is activated (green area). The purpose of Fig. 11 is not to show a result of the model but rather to illustrate all the elements involved in the calculation of the not served energy when reserved flexibility is less than needed in both time (hours) and load (MW), which is calculated in equations (9)-(13).

The amount of flexibility to activate is modeled as a short-term decision in which the DSO, with knowledge of the systems needs, activates flexibility to prevent service interruptions (i.e., energy not served). Equation (9) shows the calculation for flexibility activation at scenario s, year t, and hour h, denoted as $F^{act}_{s,t,h}$, according to the actual LDC curve, $LDC_{s,t,h}$, ensuring that the activated flexibility does not exceed the previously reserved flexibility in scenario s year t and hour h, $FC^{res}_{s,t}*T_{s,t,h}$. The amount of flexibility activated is zero if the LDC curve does not surpass the capacity limit.

$$F^{act}_{s,t,h} = \begin{cases} min(LDC_{s,t,h} - CL, FC^{res}_{s,t}*T_{s,t,h})LDC_{s,t,h} - CL \geq 0 \\ 0LDC_{s,t,h} - CL < 0 \end{cases} \forall t, s \tag{9}$$

Equation (10) shows the calculation for flexibility activation in scenario s and year t, denoted as $F^{act}_{s,t}$, by adding the flexibility activation in each hour previously calculated in equation (9).

$$F^{act}_{s,t} = \sum_h F^{act}_{s,t,h} \forall s, t \tag{10}$$

There are three possibilities for the energy not served in each year and scenario. First, there is no intervention to solve grid problems, nor flexibility, nor grid reinforcement. In this case, equation (11) shows the calculation of the energy not served, denoted as $ENS^0_{s,t}$. Second, flexibility is reserved for activation. In this case, equation (12) shows the calculation for energy not served, denoted as $ENS^F_{s,t}$. Third, if the grid is reinforced, equation (13) shows the calculation for the energy not served, denoted as $ENS^G_{s,t}$.

$$ENS^0_{s,t} = \sum_h \max(LDC_{s,t,h} - CL, 0) \forall s, t, h \tag{11}$$

$$ENS^F_{s,t} = \sum_h \max(LDC_{s,t,h} - CL - F^{act}_{s,t,h}, 0) \forall s, t \tag{12}$$

$$ENS^G_{s,t} = \sum_h \max(LDC_{s,t,h} - CL - GRC, 0) \forall s, t \tag{13}$$

This approach for determining the amount of energy not served and the flexibility to activate, using the described methodology, enables these calculations to be performed before executing the optimization model for all scenarios and years. Consequently, both the expected flexibility to be activated and the corresponding energy not served are input parameters to the optimization model. The optimization process then considers the flexibility and grid reinforcement triggers as decision variables, allowing the model to determine whether the DSO should reserve flexibility or invest in grid reinforcement at each specific year and scenario. The decision to reserve flexibility in the optimization model is constrained to ensure that no flexibility is reserved for activation in a year in which grid reinforcement is in service, see flexibility reserve constraints in Section 3.4.

The next subsection includes the formulation of the stochastic optimization model for the proposed methodology based on the real options framework.

3.4. Optimization: Mathematical formulation

This subsection describes the formulation of the stochastic optimization model, which aims to find the minimum-cost solution for the potential grid problems during the planning period by combining grid reinforcement and flexibility procurement. The stochastic optimization model's variables, objective function, and constraints are described mathematically.

The input parameters for the optimization model encompass several categories: economic parameters, grid parameters, alternative grid solutions, forecasted scenarios, and finally, the amount of flexibility to reserve/activate,[5] if any, and the energy not served under each of the three possible interventions as described in Subsection 3.3.

3.4.1. Variables

This optimization model involves four decision variables. The binary variable i^1 represents the decision to invest in grid reinforcement at the beginning of the planning period (i.e., year one). If the DSO opts not to invest in year one, the trigger level for grid reinforcement tr^G will determine future investment decisions based on evolving conditions.

The decision to reserve flexibility is also represented by two decision variables: a binary variable, f^1 which represents the decision to reserve flexibility in year one, and a trigger variable, tr^F which determines future decisions on reserving flexibility, as discussed in Section 3.2.

Furthermore, some auxiliary variables are required. These variables represent the consequences of the primary decision variables. Specifically, variable $tr^{G-act}_{s,t}$ captures grid trigger activations, taking a value of 1 when $P_{s,t-1}$ reaches or surpasses the grid trigger level tr^G and 0 when $P_{s,t-1}$ remains below the grid trigger level tr^G. Variable $i_{s,t}$ is a binary variable that takes a value of 1 if the DSO invests in the grid reinforcement in scenario s and year t, and 0 otherwise. Variable $g_{s,t}$ takes a value of 1 if the grid reinforcement is in service for scenario s and year t, and 0 otherwise.

The model also includes a variable, $r^F_{s,t}$, which indicates whether flexibility is reserved for scenario s, and year t. This variable gets a value of 1 when the peak load in scenario s at year t-1 ($P_{s,t-1}$) reaches or surpasses the trigger tr^F. On the other hand, $r^F_{s,t}$ gets a value of 0 when the peak load $P_{s,t-1}$ remains below the tr^F.

Additionally, Variable $ens_{s,t}$ represents the not served energy in each scenario s, and year t based on the selected strategy, as explained in Section 3.3.

Finally, variable $\delta_{s,t}$ takes the value of 1 when no intervention is made (i.e., the grid is not reinforced and flexibility is not reserved) to solve potential grid problems in year t, and scenario s, and 0 otherwise.

3.4.2. Objective function

The objective function (14) seeks to minimize the expected present cost during the planning period, considering four cost items:

- The cost associated with the grid reinforcement, which is represented by the expression $g_{s,t}*G^{CAPEX}$ for each scenario s, and year t. Variable $g_{s,t}$ guarantees that this expenditure is incurred when the grid reinforcement is in service. G^{CAPEX} corresponds to the annuity of the grid reinforcement investment, calculated as a series of equal payments over the asset's useful life. This annuity accounts for the asset's depreciation and the cost of capital, using the weighted average cost of capital (WACC) as the interest rate.
- The cost of reserving flexibility, which is represented by the expression $r^F_{s,t-FLT}*F^{res}_{s,t}*FR^{Cost}$. Variable $r^F_{s,t-FLT}$ guarantees that the cost of reserving flexibility is only computed if flexibility is reserved in year $t-FLT$. $F^{res}_{s,t}$ is the amount of flexibility to reserve for scenario s, and year t, expressed in MWh as explained in Section 3.2 . FR^{Cost} is the cost of reserving flexibility expressed in €/MW/h.
- The cost of flexibility activation is calculated by the expression $r^F_{s,t-FLT}*F^{act}_{s,t}*FU^{Cost}$. Variable $r^F_{s,t-FLT}$ guarantees that the cost of

[5] This flexibility is reserved, and then activated, only if there is a flexibility trigger activation in the corresponding scenario s and stage t-FLT according to the methodology described in section 3.

activating flexibility is only computed if flexibility is reserved in year $t - FLT$. $F^{res}_{s,t}$ is the amount of flexibility to activate for scenario s and year t, expressed in MWh as explained in Section 3.3. FU^{Cost} is the cost of flexibility activation expressed in €/MW/h.
- The cost of the non-served energy, which is represented by the expression $ens_{s,t}*VoLL$.

$$\min_{i^1,tr^G,f^1,tr^F} C = \sum_{t,s}\frac{1}{(1+WACC)^t}*Pr_s*\Big(g_{s,t}*G^{CAPEX} + r^F_{s,t-FLT}*F^{res}_{s,t}*FR^{Cost}* + r^F_{s,t-FLT}*F^{act}_{s,t}*FU^{Cost} + ens_{s,t}*VoLL\Big)\forall s,t \geq 1+FLT \tag{14}$$

Each scenario is weighted in the objective function according to its associated probability, Pr_s. This allows the DSO to assign higher probability to the more plausible scenarios and lower probability to less likely ones.

The weighted average cost of capital (WACC) is the discount rate used to convert all considered costs to present value.

Since current decisions only impact future years due to lead-time constraints, the early years of the planning horizon cannot be influenced by DSO decisions during the planning period. As a result, these initial stages are treated as sunk costs and are excluded from the model cost calculations. The lead time for flexibility is typically shorter than for grid reinforcement. Therefore, the objective function only considers years where $t > FLT$, as no intervention can influence earlier stages.

3.4.3. Constraints

The model constraints present the mathematical implementation of the explained methodology, divided into three groups:

- The first group includes the constraints related to the grid investment decision.
- The second group includes the constraints related to reserving flexibility.
- The third group includes the constraints related to calculating energy not served and flexibility activation.

Grid reinforcement constraints

The grid investment decision follows a trigger-based rule, where the trigger level, tr^G determines whether the investment in grid reinforcement is required. If the peak load exceeds this threshold, the grid investment decision is made, as explained in Section 3.2. At any year t and scenario s, the binary variable $tr^{G-act}_{s,t}$ takes a value of 1 if the most recent peak load observation, $P_{s,t-1}$, surpasses the grid trigger level tr^G. The activation of this trigger is governed by constraint (15), while constraint (16) ensures that no activation occurs if the peak load at t-1, $P_{s,t-1}$, remains below the trigger level. The parameter M represents a large numerical value and is used to relax constraints under certain conditions, a technique commonly known as Big M formulation [42]. The parameter ∊ represents a very small numerical value to avoid strict inequalities in the constraints.

$$tr^{G-act}_{s,t}*(M+\epsilon) - \epsilon \geq P_{s,t-1} - tr^G \forall s, 2 \leq t \leq T - GLT \tag{15}$$

$$\left(1 - tr^{G-act}_{s,t}\right)*(M+\epsilon) - \epsilon \geq t_r{}^G - P_{s,t-1}\forall s, 2 \leq t \leq T - GLT \tag{16}$$

Constraints (15) and (16) are applied within the range $2 \leq t \leq T - GLT$. Parameter T is the last year of the planning period, and parameter GLT is the lead time for grid reinforcement. As described in Section 3.2, the trigger level functions are rules for future decisions, while any present decision (t = 1), which cannot benefit from additional unfolding information, is not defined by a trigger rule, but as an independent binary variable, i^1, instead. Therefore, constraint (17) prevents any grid trigger activation at t = 1. Moreover, note that any investment decision after $T - GLT$ would result in grid reinforcement being commissioned beyond the last year of the planning period T. Therefore, such cases are excluded from this analysis. Consequently, constraint (17) also prevents any grid trigger activation after $T - GLT$.

$$tr^{G-act}_{s,t} = 0 \forall s, t > (T - GLT) \cup \mathrm{t} = 1 \tag{17}$$

The grid investment decision involves reinforcing the grid and represents a one-time commitment that can only be made once during the planning period for each scenario. This condition is enforced by constraint (18), ensuring that the investment occurs at most once per scenario.

$$\sum_t i_{s,t} \leq 1 \forall s \tag{18}$$

The decision to reinforce the grid can stem from either year 1 reinforcement decision, i^1, or from activation of the grid trigger $tr^{G-act}_{s,t}$ in case the decision comes later in the planning period.

Constraint (19) ensures that if the DSO decides to reinforce the grid at year 1, this affects all the considered scenarios.

$$i_{s,t=1} = i^1 \forall s \tag{19}$$

Constraint (20) ensures that no grid reinforcement decision is made unless the grid trigger is activated, $tr^{G-act}_{s,t} = 1$. This applies to all scenarios and all years from t = 2 onwards.

$$i_{s,t} \leq tr^{G-act}_{s,t} \forall s, t \geq 2 \tag{20}$$

Constraint (21) ensures that, for each scenario, once a trigger is activated in any year a, the grid reinforcement investment is either executed in the year a or must have already been executed in a previous year $t < a$.

$$\sum_{t=1}^{a} i_{s,t} \geq tr^{G-act}_{s,t=a} \forall s, a \tag{21}$$

Since the decision to reinforce the grid in year 1 is controlled by variable, i^1, and the grid trigger activation does not influence the decision this year, constraint (22) ensures that no trigger activation occurs during year 1.

$$tr^{G-act}_{s,t=1} = 0 \forall s \tag{22}$$

Grid reinforcement has an associated lead time, from the decision to reinforce the grid until the reinforcement is in service. Once the grid reinforcement is in service in a particular scenario, it remains in service for the rest of the planning period. This process is governed by constraint (23), ensuring that for any year a of the planning period, if the grid reinforcement decision has been made, the grid reinforcement must have entered service in year $a - GLT$. Variable $g_{s,t}$ takes a value of 1 when the grid reinforcement has entered service at a given scenario and year; otherwise, it remains at 0.

$$g_{s,t=a+GLT} = \sum_{t=1}^{a} i_{s,t} \forall s, a \leq T - GLT \tag{23}$$

The earliest year for deciding to reinforce the grid is t = 1, in that case, the reinforcement would be operational at year $t = GLT + 1$. Then Constraint (24) ensures that no grid reinforcement enters into service earlier than that.

$$g_{s,t} = 0 \forall s, t \leq GLT \tag{24}$$

Flexibility reserve constraints

The decision to reserve flexibility also follows a trigger-based rule. The trigger level, tr^F determines whether flexibility reserve is reserved. The DSO reserves flexibility if the peak load exceeds this threshold, as explained in Section 3.2. At any year t and scenario s, the binary variable

$r^F_{s,t}$ takes a value of 1 if the most recent peak load observation, $P_{s,t-1}$, reaches or surpasses the grid trigger level tr^F, this is governed by equation (25), which also ensures that no flexibility is reserved if grid reinforcement is already scheduled for commissioning in year $t+FLT$ (i.e., $g_{s,t+FLT}=1$). While constraint (26) ensures that no flexibility reserve occurs if the peak load at t-1, $P_{s,t-1}$, remains below the trigger level. The parameter M represents a large numerical value as previously explained. The parameter epsilon represents a very small numerical value to avoid strict inequalities in the constraints.

$$\left(r^F_{s,t}+g_{s,t+FLT}\right)*(M+\epsilon)-\epsilon\geq P_{s,t-1}-tr^F\forall s,2\leq t\leq T-FLT \tag{25}$$

$$(1-r^F_{s,t})*(M+\epsilon)-\epsilon\geq tr^F-P_{s,t-1}\forall s,2\leq t\leq T-FLT \tag{26}$$

Constraints (25) and (26) are applied within the range $2\leq t\leq T-FLT$. As described in Section 3.2, the trigger level serves as a rule for future decisions, while any present decision (t = 1), which cannot benefit from additional unfolding information, is not defined by a trigger rule, but as an independent binary decision. The decision to reserve flexibility at year 1, denoted as f^1, applies to all scenarios at once; this condition is enforced by constraint (27).

$$r^F_{s,t=1}=f^1\forall s \tag{27}$$

Note that any reservation of flexibility after $T-FLT$ would result in flexibility being available for activation beyond the last year of the planning period T. Therefore, such cases are excluded from this analysis. Consequently, constraint (28) ensures no flexibility reservation occurs after $T-FLT$.

$$r^F_{s,t}=0\forall s,t>T-FLT \tag{28}$$

Finally, flexibility cannot be reserved at year t for activation in year $t+FLT$ if grid reinforcement is already scheduled for commissioning in $t+FLT$ (i.e., $g_{s,t+FLT}=1$). This assumption is based on the premise that the considered grid reinforcement fully addresses all potential network congestion throughout the planning horizon. Constraint (29) ensures compliance with this condition.

$$r^F_{s,t}\leq 1-g_{s,t+FLT}\forall s,1\leq t\leq T-FLT \tag{29}$$

Flexibility activation and energy not served constraints

The objective function of this model is to try to minimize the energy not served, as it increases costs. Taking this into account, Constraint (30) ensures that the energy not served corresponds to the intervention made in each scenario and year, $ENS^0_{s,t}$, if no intervention is made, $ENS^F_{s,t}$, if flexibility is reserved, and $ENS^G_{s,t}$, if grid reinforcement is commissioned according to Section 3.3. This equation corresponds to a single-node capacity-limited network model.

Constraint (31) ensures that variable δ takes a value of 1 when no intervention is made at each year t and scenario s.

$$ens_{s,t}\geq ENS^0_{s,t}*\delta_{s,t}+ENS^F_{s,t}*r^F_{s,t-FLT}+ENS^G_{s,t}*g_{s,t}\forall s,t\geq 1+FLT \tag{30}$$

$$r^F_{s,t-FLT}+g_{s,t}\geq 1-\delta_{s,t}\forall s,t\geq 1+FLT \tag{31}$$

Considering more complex network models (e.g., multi-node models with voltage operational limits) would require additional constraints, such as enforcing power flow equations between nodes and enforcing the desired technical performance metrics. The model may also be extended to consider additional reinforcement alternatives by adding more variables that represent the different possible interventions.

4. Case study

This section presents a case study to illustrate the proposed methodology. The case study consists of a constrained substation in a distribution network. This substation has a capacity limit of 60 MW. There are two possible interventions to solve potential grid constraints.

- First, reinforce the grid by building a new feeder that redirects part of the load (a maximum of 20 MW) to an adjacent substation. The new feeder entails an investment of 432 k€, with a useful life of 40 years, and a three-year commissioning lead time.[6]
- Second, contract flexibility from connected users. There are 4 MW of maximum available flexibility each year for the planning period, whereas the amount of flexibility to reserve is optimized based on the methodology explained in Section 3.2, never exceeding the available flexibility. This 4 MW value corresponds to approximately 7% of the peak load in year 0 (57.7 MW) and is consistent with estimates reported in previous studies (6%) [10] and real DSO experience (8%) [11]. Since the available flexibility depends on local conditions, a sensitivity analysis is performed in Section 5.2, where it varies between 1 MW and 8 MW. The cost for reserving flexibility is 33.35 €/MW/h, and the cost for flexibility utilization is 200.68 €/MWh based on [9].[7] The considered lead time for flexibility is one year.

The weighted average cost of capital (WACC) is 5.58%,[8] and the value of lost load is 4370 €/MWh.

4.1. Scenarios for peak load evolution

The scenarios for peak load evolution are taken from the "Future Energy Scenarios 2023" elaborated by National Grid in the UK [2]. The DSOs usually adapt these national forecast scenarios and use other inputs to produce forecasts in a particular distribution network region. Then, the DSO uses these forecasts to perform a cost-benefit analysis, as shown in [11], in which the forecasted scenarios, or at least part of them, are based on the National Grid projections. In this case study, we consider a 10-year planning horizon. We adapted the 2023 peak demand forecast from National Grid [2] to the proposed case study by transforming the national-level forecasted peak load, in GW, to MW for our case study (see Table 2).

The four base scenarios (b1, b2, b3, and b4) represent long-term uncertainty. Then, we use a Monte Carlo simulation to add noise to these scenarios, representing the short-term uncertainties, as explained in the methodology. The increase or decrease in the materialized noise is modeled as a normal distribution with a mean of 0 and a standard deviation of 0.4%.

The scenario generation procedure starts by setting the random seed to 0 to ensure reproducibility. A total of 160 scenarios are generated, organized into 40 scenarios for each of the four base scenarios (b1, b2, b3, and b4).

To construct each of the 160 scenarios, the peak-load trajectory in the base scenario is used as a reference. At each time step, the growth rate of the peak load between two consecutive points in the base scenario is first computed. This growth rate is applied to the simulated series at the previous time step. Then, a random noise term is added, modeled as a normally distributed variable with a mean of 0 and a standard deviation equal to 0.4% of the peak load at that step.

In this way, each simulated scenario represents a plausible evolution of the peak load, starting from the same base trajectory and subject to noise-induced variations.

For instance, in base scenario b1, the initial peak load at t = 0 is 57.7 MW. Between t = 0 and t = 1, the base trajectory decreases by 0.9 MW,

[6] The International Energy Agency indicates in [45] that the lead time for investments in the distribution network in Europe varies between 2 and 4 years.

[7] Average availability and utilization payments from February 2021 tender based on the report by Aurora Energy Research [9]. Conversion rate considered 1.15 Euro/GBP.

[8] 5.58% is the WACC established by the Spanish regulator CNMC [46].

Table 2
Peak load scenarios (MW).

	Year										
	0	1	2	3	4	5	6	7	8	9	10
b1	57.7	56.8	57.2	58.1	58.9	60.4	62.9	65.9	68.5	71.5	75.2
b2	57.7	58.0	58.2	58.4	58.9	59.6	60.6	62.1	63.3	64.9	66.8
b3	57.7	56.2	54.9	55.0	55.9	57.0	59.0	60.7	62.8	66.3	69.7
b4	57.7	61.0	61.8	62.8	63.5	64.4	65.1	66.1	67.4	69.0	70.8

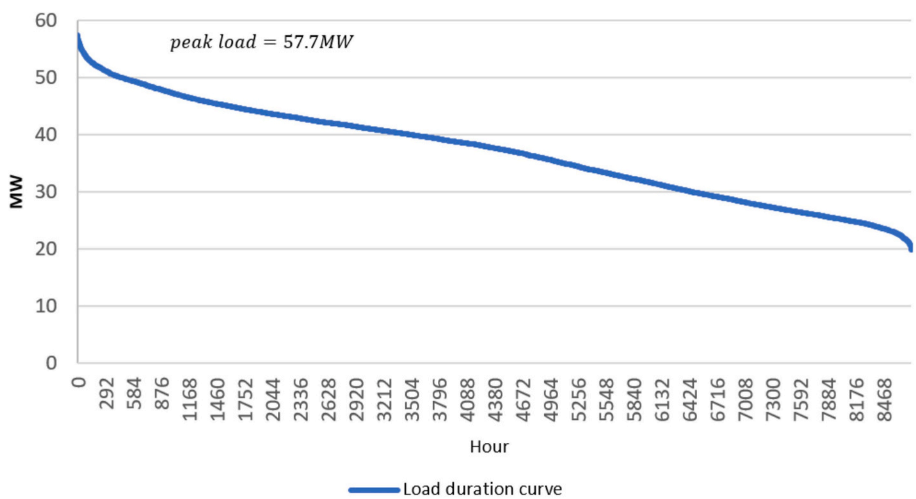

Fig. 12. Load duration curve at year 0 used for the case study.

which corresponds to a negative growth rate of 1.56%. Applying this growth rate to the initial value yields 56.8 MW. At this stage, a noise term sampled from a normal distribution with a mean of 0 and a standard deviation of 0.2272 MW (i.e., 0.4% of the peak load) is added; the noise results in −0.04 MW, resulting in a value of 56.76 MW for $t = 1$ in this illustrative case. Between $t = 1$ and $t = 2$, the base scenario grows from 56.8 MW to 57.2 MW, equivalent to a 0.704% growth rate. Applying this growth rate to the simulated 56.76 MW at $t = 1$ gives 57.16 MW, to which noise sampled from a normal distribution of mean 0 and standard deviation 0.2286 is added, yielding 57.17 MW as the simulated value for $t = 2$. This procedure is repeated across all subsequent time steps to generate the complete set of scenarios. The dataset for the peak load of the 160 scenarios is included in the supplementary material.

This noise may be modeled using any other probability distribution function, depending on the needs of the particular case study.

4.2. Load duration curve

Fig. 12 shows the load duration curve for the substation under study in year 0 with a peak load of 57.7 MW. The assumption is that this load duration curve will maintain its form, having the same growth rate as the peak load for every hour, as explained in Subsection 3.2. The load duration curve is based on hourly data combining demand, PV, and wind generation profiles collected for 2019 from the Spanish Transmission System Operator database [43]. The resulting LDC used in this case study is available in the supplementary material.

5. Results and discussion

Section 5.1 presents the results of the methodology applied to the case study, showing the potential economic efficiencies of the adaptable planning strategy. Section 5.2 presents a sensitivity analysis to test the results under different conditions (i.e., variations in flexibility availability and flexibility cost). All simulations were implemented in Python 3.13.[9] The optimization solver used was Gurobi Optimizer 11.0.3.[10] The experiments were executed on a laptop running Windows 11 with 16 GB RAM and an Intel i7 processor. The execution time for the optimization model in the case study shown in Section 5.1 was 3.63 s.

Table 3
Results of the adaptable planning approach proposed in this study versus the traditional planning approach.

	Strategy	Results
Proposed Methodology	$f^1 = 1tr^F = 56.55$ MW $i^1 = 0tr^G = 56.57$ MW Grid investment year:$(2 - 7)$	Expected Present Cost: 112.1 k€ Expected ENS: 1.38 MWh Expected Flexibility reserve: 266.4 MWh Expected Flexibility activation: 59.2 MWh
Traditional Approach	$g^{year} = 6f^{years} = (2-5)$Grid investment year: 3	Expected Present Cost: 132.1 k€ Expected ENS: 2.61 MWh Expected Flexibility reserve: 758.9 MWh Expected Flexibility activation: 75.1 MWh

5.1. Case study results

Table 3 presents the case study results obtained by applying the methodology proposed in this article. These results are compared with those from a traditional planning approach, in which the DSO seeks to

[9] https://www.python.org/.
[10] https://www.gurobi.com/solutions/gurobi-optimizer/.

minimize the expected cost across the planning period using a fixed-decision methodology. In this traditional approach, another stochastic optimization model is executed in which the DSO directly decides the year for grid reinforcement. This model is a simplified version of the one presented in Section 3.4. Unlike the proposed real options approach, it does not use triggers as decision variables. Instead, the year for grid reinforcement is a single decision that applies to all scenarios. Similarly, the decision to reserve flexibility is not scenario dependent.

As a consequence, the simplified model does not include the trigger-related constraints (15), (16), (17), (20), (21), (22), (25), and (26), nor constraints (19) and (27), which are required to represent adaptable planning decisions. The objective function (14) remains unchanged, as do constraints (18), (23), (24), (28), (29), (30) and (31), with the only difference being that the variable representing the decision to reserve flexibility $r^F_{s,t}$, does not contain the scenario subindex resulting in r^F_t, as well as the variable representing the investment decision, $i_{s,t}$, and commissioning $g_{s,t}$, which result in i_t and g_t in the simplified model, reflecting the fact that decisions are no longer scenario-dependent.

In this case, as a result of the optimization model under the traditional approach, the DSO chooses to reinforce the grid at the beginning of the 3rd year, entering into service in year 6, $g^{year} = 6$. Flexibility is reserved for activation in years 2 to 5, $f^{years} = (2-5)$.

In contrast, the proposed real options methodology uses decision rules defined as triggers, tr^F and tr^G, for flexibility reserve and grid investment respectively. These triggers may result in different investment decisions for each scenario based on unfolding information during the planning period, taking advantage of the real options thinking.

In the traditional approach, the amount of flexibility reserved (MW) corresponds to the maximum expected peak load for the year in which flexibility is to be activated. For example, Table 2 presents the base scenarios, showing that the maximum expected peak load in year 2 is 61.8 MW, 1.8 MW over the capacity limit. Therefore, if the DSO decides to reserve flexibility in year 1 for activation in year 2, the DSO will reserve 1.8 MW of flexibility. The time during which flexibility is reserved follows the real options approach explained in the methodology. Specifically, it involves projecting the load duration curve for a peak of 61.8 MW and calculating the time the LDC exceeds the capacity limit, as described in Subsections 3.2 and 3.3.

Results show that the real options approach reduces the expected cost by 15.1% compared to the traditional approach for the tested scenarios. The real options approach reduces the expected flexibility to reserve by 64.9% and the expected flexibility to activate by 21.2%. The expected energy not served decreases by 1.23 MWh for the proposed methodology compared to the traditional approach. This difference in the expected energy not served is a result of the short-term uncertainty leading to unexpectedly high peak load in some scenarios, which is better captured by the adaptable strategies as the amount of flexibility to reserve adjust to each scenario unfolding information during the planning period.

One interesting result is the timing of the investments across the different scenarios. Table 4 summarizes the timing of the grid reinforcement and the use of flexibility for some representative case study scenarios. The strategy selected by the proposed methodology resulted in $f^1 = 1$, meaning that flexibility is reserved in year 1; since flexibility lead time is one year, this flexibility is reserved for activation during year 2, which is why the year 2 column is filled in blue[11] in Table 4. After year 2, flexibility is reserved according to the flexibility trigger, denoted as tr^F. It may happen that the peak load surpasses the flexibility trigger, and the calculation of flexibility to reserve results in 0 MWh, as explained in Subsection 3.2. In such cases, the cell is not filled in blue as flexibility is not reserved. Cells filled in green indicate that the grid reinforcement is in service for that year and scenario. The grid reinforcement enters into service in year 5 for scenarios 1, 41, and 121, and year 9 for scenario 81. On the other hand, in the traditional approach, the grid reinforcement enters into service in year 6 for all scenarios. As a result, the proposed approach anticipates investments compared to the traditional approach in some scenarios (e.g., scenarios 1 and 41), and it delays grid reinforcement in others (e.g., scenario 81). An investment plan with trigger rules for investment decisions allows the regulator to conditionally approve a particular investment based on the same trigger rule. For example, the investment in a new feeder can be pre-approved, but final approval is subject to the same trigger condition that confirms the need for reinforcement under the plan (e.g., if the peak load reaches or exceeds a threshold). This is why the real options approach may serve as a basis for the conditional approval of anticipatory investments, striking a balance between enabling faster connections and ensuring economic efficiency.

Full results of the real options approach are provided in the supplementary material, including the planning actions taken across all scenarios to ensure replicability. Results confirm that the trigger-based decision-making has been correctly implemented, as the model's resulting decisions are consistent with the optimized trigger levels presented in Table 3. For example, the trigger for grid reinforcement is set at 56.57 MW. In scenario 81, the peak load surpasses this threshold in year 5 (note that year 0 is excluded from trigger activation according to the methodology). Consequently, at the beginning of year 6, the decision is made to reinforce the grid with a new feeder. Considering the three-year lead time, the reinforcement is commissioned at the beginning of year 9.

Table 5 summarizes the differences in timing for grid reinforcement between the proposed and traditional approaches. The proposed approach anticipates investments in 73.1% of scenarios, compared to the traditional approach. At the same time, the grid reinforcement is deferred in 25.7% of the scenarios compared to the traditional approach. Overall, the proposed approach results in more cost-effective solutions by making investments only when necessary, thereby reducing the risk of stranded assets. It is important to note that the proposed approach results in an expected commissioning time for grid reinforcement (year 6.04 across all scenarios), similar to the traditional approach (year 6) for this case. At the same time, Table 3 shows a significant reduction in the use of flexibility under the proposed approach (64.9% reduction in flexibility reserve and 21% reduction in flexibility activation), highlighting its more efficient use of flexibility resources.

The results showed that the real options approach yields lower costs while using less flexibility, giving more value to the flexibility solutions[12]. This highlights the synergy between the real options framework and the flexibility solutions. Adaptable strategies enable the selective use of flexibility, using more in scenarios where it offers greater value, and opting instead for grid reinforcement in scenarios where it becomes more cost-effective.

5.2. Sensitivity analysis: The effect of flexibility price and availability

Flexibility providers may offer varying volumes of flexibility at different costs, influenced by several factors such as the availability of flexible resources at a given location, network topology, and regulatory conditions. Therefore, it is valuable to test whether the case study results remain consistent under different flexibility cost and availability assumptions.

Fig. 13 presents the cost reduction achieved by the proposed real options approach relative to the traditional approach under different conditions. Since the expected present cost under the real options approach for the base case is 112.1 k€ (Table 3) and the cost under the traditional approach is 132.1 k€, this represents a 15.1% cost reduction.

[11] Dark blue indicates that the reserved flexibility is finally activated and light blue that flexibility is reserved and not activated.

[12] Note that expected costs are exactly the same in both the proposed and the traditional approach when flexibility is unavailable.

Table 4
Example of the reserve and use (or not) of flexibility and the commissioning of grid reinforcement for the proposed approach in the case study.

		Year (stage) t										
		0	1	2	3	4	5	6	7	8	9	10
Real options approach	1	57.70	56.76	57.17	58.23	59.01	60.85	62.98	66.06	68.33	71.31	74.91
	…											
	41	57.70	58.04	57.90	57.83	58.39	59.00	59.81	61.27	62.54	63.96	65.40
	…											
	81	57.70	56.22	54.93	54.98	56.11	57.49	59.54	61.24	63.64	67.58	70.74
	…											
	121	57.70	61.08	62.08	62.84	63.49	64.68	65.58	66.61	67.75	69.62	71.94
	…											
Trad. Approach	1-160	…	…	…	…	…	…	…	…	…	…	…

*Light blue fill: flexibility is reserved and not activated for that scenario and stage.
**Dark blue fill: flexibility is reserved and activated for that scenario and stage.
***Green fill: grid reinforcement in service for that scenario and stage.

Light blue fill: flexibility is reserved and not activated for that scenario and stage.
Dark blue fill: flexibility is reserved and activated for that scenario and stage.
Green fill: grid reinforcement in service for that scenario and stage.

Table 5
Results for timing of grid reinforcement across scenarios in the proposed approach.

	Proposed approach	Traditional approach
Grid reinforcement enters into service	year 5 (75.6% of scenarios) year 6 (0.6% of scenarios) year 8 (3.1% of scenarios) year 9 (16.3% of scenarios) year 10 (4.4% of scenarios)	year 6

The flexibility available in this analysis ranges from 1 MW (25% of the initial value) to 8 MW (2 times the initial value). Similarly, the cost of flexibility ranges from 8.34 €/MW/h for the reserve cost and 50.17 €/MWh for the activation cost (25% of the initial value) to 66.7 €/MW/h for the reserve cost and 401.36 €/MWh for the activation cost (twice the initial value).

Results show that the savings achieved with the real options approach remain consistent across the sensitivity analysis, exceeding 10% in most scenarios. In cases where flexibility availability is very low (i.e., 1 MW), the results are similar to those of the traditional approach. This further underscores the synergy between the real options approach and flexibility solutions, as the benefits of the real options methodology become more evident when more flexibility is available. This synergy was expected, as anticipated in Sections 1 & 2, further validating the proposed model.

Fig. 14 and Fig. 15 present error bars representing one standard deviation of the expected cost in the case study under variations of flexibility cost and flexibility availability, respectively, for both the real options and traditional planning methodologies. Fig. 14 shows that the bars for the real options approach (blue) remain consistently below those of the traditional methodology (orange) across variations in flexibility cost, indicating the robustness of the savings generated by the real options approach. The largest cost differences are observed at the lower bound of the error bars, suggesting that the real options approach produces substantial savings in a subset of scenarios. This finding is consistent with the results presented in Table 5, where investment deferral under the real options approach (compared to the traditional approach) occurred in approximately 25% of the scenarios, corresponding to those with the highest savings. Fig. 15 shows a pattern similar to Fig. 14, further highlighting the robustness of the results under variations in flexibility availability (Fig. 13).

6. Limitations of the study

Although the study presents a valuable methodology and relevant insights, certain limitations must be acknowledged. First, using the LDC to calculate flexibility reserve and activation overlooks chronological time dependencies, which are particularly important when modeling batteries as flexible resources. Their charging and discharging constraints are time-dependent, and this is overlooked when using an LDC. In further research, the modeling of distributed generation and load variability using daily curves would be investigated. Second, the model assumes a fixed price for flexibility contracts (both for reserve and activation) and fully reliable provision of the service. In practice, however, local flexibility markets may exhibit limited liquidity and strategic bidding behavior, leading to increasing, potentially volatile prices, especially as demand for flexibility grows. This means the assumed linear relationship between flexibility volume and flexibility cost may not hold. Higher flexibility demand, assuming a constant supply portfolio, would require clearing progressively more expensive offers in the market, thereby increasing the average cost of flexibility. This limitation could be addressed in future formulations of the presented model. However, this limitation does not affect the main conclusions of the paper. As shown in the results in Section 5.1, the traditional approach requires higher levels of flexibility demand in both reserve and activation to achieve a similar expected investment deferral across scenarios.

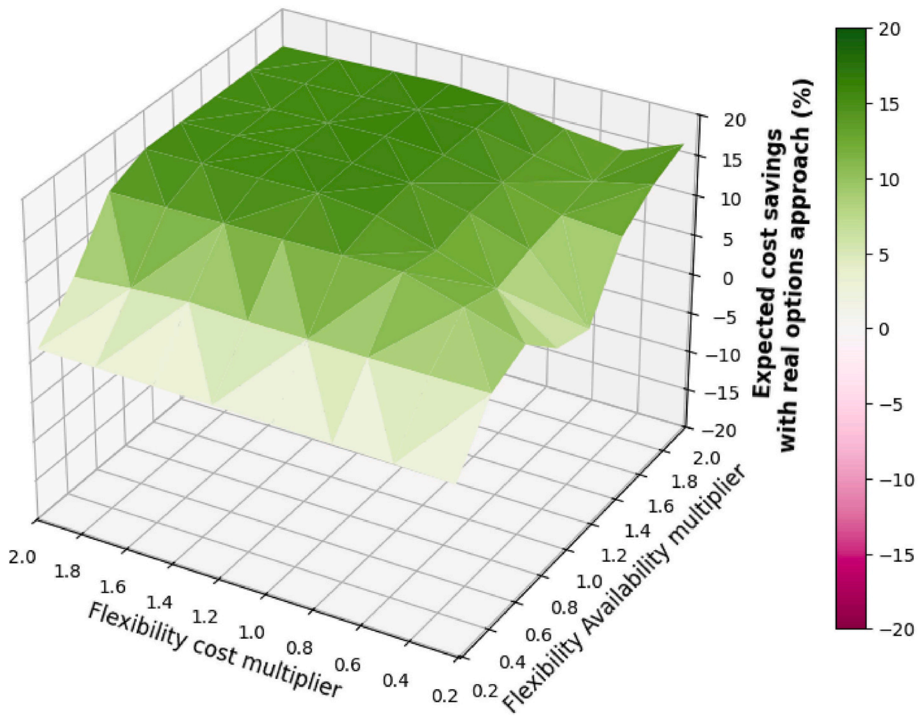

Fig. 13. Sensitivity of expected cost savings (%) with the real options approach compared to the traditional approach.

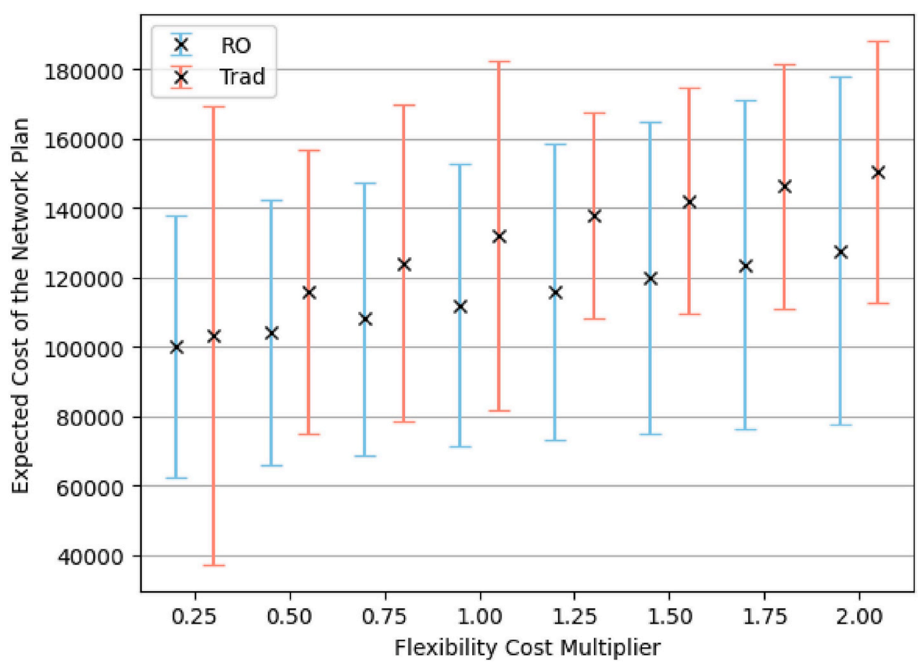

Fig. 14. Error bars (1 std dev.) for expected cost savings under variations in flexibility cost. Real options approach (blue) compared to traditional approach (orange).

This indicates a less efficient use of flexibility than in the proposed approach. Therefore, if the relation between flexibility cost and volume were non-linear, the traditional approach would likely be affected more severely. Consequently, the proposed real options approach may have an additional advantage over the traditional one when the non-linear relationship between flexibility volume and cost is considered. Regarding the reliability of flexibility provision may be explicitly included in the model formulation. These limitations may be addressed in future work by refining the presented formulation. The results remain valid for drawing conclusions about the application of the proposed real options approach to assessing investments in distribution substation capacity.

7. Conclusions

This article highlights two key considerations when implementing real options thinking to assess investments in the distribution network. First, representing uncertainty in a way that fits the problem, far from the GBM assumptions commonly used in the financial world. Second, the approach should result in actionable plans by defining decision rules for

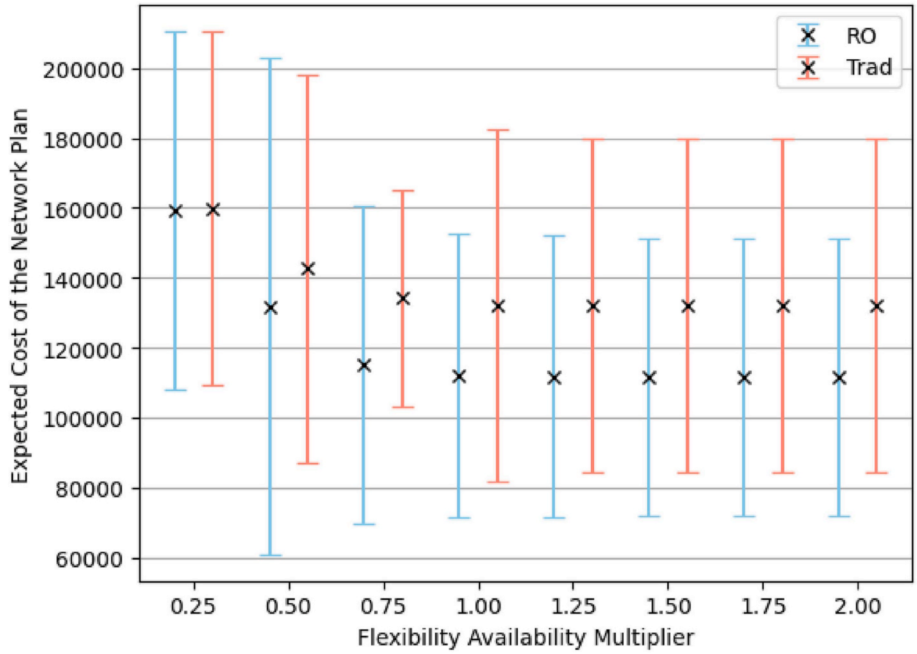

Fig. 15. Error bars (1 std dev.) for expected cost savings under variations in flexibility availability. Real options approach (blue) compared to traditional approach (orange).

the adaptable strategies.

The methodology presented in this article highlights the potential efficiency of the adaptable planning approach for assessing investment in the distribution substation capacity under uncertainty when flexibility solutions are available. The tested scenarios demonstrate that combining flexibility solutions with the proposed real options framework can significantly reduce costs. The resulting adaptable strategy, with optimized trigger levels, allows deferring grid investments in some scenarios while anticipating them in others, in contrast to the traditional approach that relies on fixed decisions. This adaptability is particularly valuable given the current uncertainty faced by Distribution System Operators (DSOs).

This work proposes a trigger rule definition that allows the formulation of a multi-stage, multi-scenario mathematical optimization model based on the real options approach. This trigger rule definition and the mathematical optimization model constitute a rigorous implementation of the real options thinking to DNP, unlike previous optimization models presented in the literature. The intuitive definition of trigger rules captures how DSOs make their planning decisions, resulting in practical, implementable investment strategies that may serve as a foundation for regulators to conditionally approve anticipatory investments. The mathematical optimization approach avoids the use of metaheuristics, resulting in a tractable model.

As a consequence, the proposed approach provides a foundation for assessing the timing of anticipatory investments by enabling conditional approval of grid reinforcements based on the trigger levels. This facilitates a balance between allowing faster user connections by anticipating grid reinforcement in some scenarios and achieving economic efficiency, leveraging the increased flexibility in distribution networks enabled by distributed energy resources. Results show that the adaptable strategy can extract greater value from flexibility than traditional discounted cash flow approaches with fixed decision-making. This advantage becomes even more relevant as the availability of flexibility increases. Moreover, the methodology continues to deliver substantial savings, with expected cost reductions of 10% to 16% in most scenarios, even when flexibility comes at a high cost.

Future research could extend this framework as part of a sequential approach to solve larger-scale network planning problems with full network representation. While the present work adopts a simplified network representation, the focus on substation capacity expansion addresses a highly relevant planning problem due to the high cost of these investments and the importance of accurately determining their timing.

In this approach, a traditional plan can be computed for a realistic distribution network to identify the locations and sizes of investment candidates across the system. Subsequently, the proposed methodology could be applied to selected investment candidates (i.e., substation capacity expansions), enabling adaptable investment strategies to better time these investments. The individual assessment of investment projects is a requirement for DSOs when justifying investment needs and their timing to regulators.

The presented work assumes a cost-minimizing strategy. However, the distribution network is considered a regulated monopoly, and the DSO's revenues are regulated. DSOs may have incentives that are not aligned with cost-minimization, such as a cost-of-service regulatory framework. Future work may model different regulatory frameworks for remuneration of distribution and provide regulatory recommendations to incentivize the DSO to adopt adaptable planning strategies, thereby leading to cost minimization.

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CRediT authorship contribution statement

Miguel A. Ruiz: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Tomás Gómez:** Writing – review & editing, Visualization, Supervision, Conceptualization. **José P. Chaves:** Writing – review & editing, Visualization, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Miguel A. Ruiz reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2026.112110.

Data availability

I have shared the data in the supplementary material.

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