

# Expansion planning of the transmission network with high penetration of renewable generation: A multi-year two-stage adaptive robust optimization approach

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## ABSTRACT

This paper addresses the multi-year two-stage expansion planning of the transmission network of a power system with high penetration of renewable generation modeling long-term uncertainty by using adaptive robust optimization. The multi-year nature of the problem is modeled by considering a comprehensive view of the planning horizon. A cardinality-constrained uncertainty set is used to model the future worst-case uncertainty realization of the peak power consumption of loads, along with the capacity and marginal production cost of generating units. Unlike previous works, we model certain features of the operation that are typically ignored in multi-year robust transmission network expansion planning problems, namely, the operational variability of renewable generating units, the operational flexibility of conventional generating units, and the non-convex operational feasibility sets of storage facilities. The solution procedure employed for this multi-year two-stage robust problem, which is formulated as a three-level problem, is based on the combination of the nested column-and-constraint generation algorithm with two exact acceleration techniques. We analyze the performance of the proposed model through the use of the IEEE 24-bus Reliability Test System and the IEEE 118-bus Test System. Numerical results show that the use of the multi-year approach leads to reductions in the total worst-case cost of up to 7% in comparison with the static and sequential static procedures. Moreover, an underestimation of the total worst-case cost of more than 8% is attained when ignoring certain operational constraints of conventional generating units and storage facilities. Lastly, a sensitivity analysis is presented in order to illustrate the impact of the maximum deviations of the uncertain parameters on the total worst-case cost.

## 1. Introduction

This paper addresses the transmission network expansion planning problem (TNEP), which is solved by the transmission system operator (TSO) in order to determine the investment plan that minimizes the total cost under a centralized framework, i.e., the sum of the investment costs associated with the construction of new transmission lines and the operating costs related to the production of generating units and the load shedding [1].

### 1.1. Motivation

Future power systems are expected to undergo major changes in order to fulfill political requirements, namely, the objective of limiting

the increase in the global average temperature to 2 °C in comparison with pre-industrial levels established in the Paris Agreement [2] and the goal of the European Commission of being climate-neutral by 2050 [3]. Although CO<sub>2</sub> emission constraints and taxes can be imposed in expansion planning problems [4], an increase in the percentage of the total production in the electricity mix of power systems supplied by weather-based renewable generating units is also needed to attain these targets. Note that weather-based renewable production of solar and wind-power units can be exploited on a large scale in locations that are generally isolated from the transmission network or far away from demand centers [5]. Hence, the future high incorporation of renewable energy resources into power systems, together with the expected rise in the power consumption of loads and the aging of the transmission

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network, put the supply of the loads at risk, i.e., load shedding may occur. It is, therefore, necessary to identify which reinforcements should be made in the transmission network by the TSO in order to ensure the quality of the supply.

The intrinsic operational variability of the weather-based renewable production can be modeled by using aggregation techniques to group the historical data concerning solar- and wind-power production into a set of representative days (RDs) [6], each of which is composed of a number of representative time periods (RTPs). A trade-off between the complexity of the expansion planning problem and the accuracy of the characterization of the operational variability should be sought since the number of RDs considered influences the expansion decisions of the power system identified by using mathematical optimization techniques [7], but increases in the total number of RDs translate into more variables and constraints involved in the problem and, therefore, greater computational times [8]. Note that the presence of storage facilities is a key aspect in TNEP problems since the TSO could benefit from the presence of storage facilities attached to certain locations in terms of building fewer transmission lines [9]. Moreover, modeling the operational flexibility of conventional generating units through their ramping limits and commitment statuses is important as well to avoid suboptimal solutions in expansion planning problems [10].

In this paper we assume a two-stage framework of the TNEP problem, i.e., expansion decisions are identified at the first stage when the future conditions are unknown, and operating decisions are made at the second stage after the uncertainty realization has occurred. It should be stressed that modeling the uncertainty is a key aspect since suboptimal solutions may be determined when it is assumed that the TSO has perfect information on the unknown future conditions [11]. We focus on modeling long-term uncertainties such as the capacity of renewable generating units and the peak power consumption of loads, among others. These uncertain future conditions of the power system are specifically modeled by using robust optimization [12]. This is a method to solve decision-making problems under uncertainty in which the values of the uncertain parameters vary within predefined intervals. Note that the limits of these intervals are also known as confidence bounds. The solution associated with the worst-case situation is provided when robust optimization is used. Thus, robust optimization can be applied to protect the power system under the worst-case uncertainty realization of future conditions, which is identified as the uncertainty realization within an uncertainty set that maximizes the operating costs. Moreover, adaptive robust optimization (ARO) [13], also denominated as robust optimization with recourse, prevents too conservative solutions by taking corrective actions associated with the second stage of the TNEP problem, also called recourse decisions, after the worst-case uncertainty realization is identified.

Furthermore, the TSO analyzes the TNEP problem by considering a planning horizon that may cover several decades. With regard to the timing at which new transmission lines should be built, three different approaches can be considered:

1. A multi-year approach, in which the TNEP problem is solved by considering that the expansion planning decisions can be made at any time throughout the planning horizon [14–16]. The main issue of this framework is that it generally involves computationally intractable problems owing to its high complexity.
2. A static approach, in which all investment decisions are made at the beginning of the planning horizon in order to reduce the complexity of the TNEP problem [17–19]. In this approach, a target year is considered, namely, the last year of the planning horizon, since it is expected that this year will involve the most difficult conditions to ensure the operating feasibility of the power system. Nevertheless, the static approach does not allow the planner to adjust the expansion decisions to future changes in the power system. Thus, a multi-year approach generally involves better decisions than a static approach does, since the building of new transmission lines is delayed until they are really needed.

3. A sequential static approach, also known as pseudo multi-year procedure [20], which involves sequentially facing static TNEP problems for different target years. In turn, this approach is divided into forward and backward procedures [20]. On the one hand, the forward procedure implies that static TNEP problems are consecutively solved for each year starting from the first year, where the expansion decisions obtained in one of these problems are considered as existing facilities of the following problems. On the other, the backward procedure consists in solving the static TNEP problem for the last year, and the planner then tries to anticipate when the investment decisions should be made in order to ensure the operating feasibility in previous years. However, this approach presents the drawback of losing the global viewpoint of the planner since, in general, the solution of the multi-year planning problem does not match the collection of solutions obtained from the sequential static planning problems. This approach leads, therefore, to a trade-off between the complexity of the problem and its accuracy.

Keeping this context in mind, the aim of this paper is to develop a multi-year ARO TNEP model that considers high penetration of renewable generation and represents the operational variability and certain features that are typically ignored in the technical literature, namely, the inter-temporal and non-convex operational feasibility sets of storage facilities and conventional generating units. Note that the operational feasibility sets of storage facilities and conventional generating units are non-convex since binary variables are used to prevent the simultaneous charging and discharging of the former and to model the commitment statuses of the latter. The high complexity of the resulting problem is mitigated in this paper by combining an exact decomposition technique with two exact acceleration techniques, which ensures the converge to the global optimal solution in a finite number of steps.

## 1.2. Literature review

Several works have been proposed to address two-stage ARO expansion planning problems in the technical literature. The two-stage ARO TNEP problem is addressed in [21] by applying Benders decomposition [22], where the master problem minimizes the investment costs and the subproblem minimizes the maximum curtailment of load and renewable generation subject to the uncertainty in the net injections. The authors of [17,23] model the two-stage ARO TNEP problem by applying the column-and-constraint generation algorithm (CCGA) [24] and recast the max–min subproblem as an equivalent single-level optimization problem through the use of the Karush–Kuhn–Tucker (KKT) necessary optimality conditions. Two approaches to identify the worst-case uncertainty realization of the middle-level problem are compared in [17], namely, the maximization of operating costs and the maximization of the regret related to the potential cost savings of the planner. In addition, the authors of [23] propose the use of a polyhedral uncertainty set [25], where a parameter denominated as the uncertainty budget is used to control the degree of conservativeness, considering that the uncertain variables may be constrained by regional uncertainty budgets. Moreover, the two-stage ARO TNEP problem is also tackled in [26] by applying the CCGA, but more computationally efficient solutions are obtained by using the Lagrangian duality theory to recast the two lowermost optimization levels as an equivalent single level. Additionally, the authors of [26] consider a cardinality-constrained uncertainty set [25], in which the number of uncertain parameters that may undergo deviations from their nominal values is limited by an uncertainty budget that takes integer values, and point out the difficulties to interpret the results associated with intermediate values of the uncertainty budgets of the uncertainty set proposed in [23]. The two-stage ARO transmission and energy storage expansion planning problem is formulated in [18] by using RDs to characterize

the operational variability, while first-stage binary decision variables are considered to model transmission line switching and the charging/discharging statuses of storage facilities. Note that these decisions should be modeled by using second-stage binary variables rather than first-stage binary variables since they are made once the realization of the future uncertain conditions of the power system is known. It should be stressed that the prevention of the simultaneous charging and discharging of storage facilities may avoid suboptimal expansion decisions as shown in [27], which is likely to occur in the solution determined by using expansion planning models with linear constraints for the operation of storage facilities when renewable-dominated power systems are analyzed [28].

The authors of [19] propose applying the alternating direction algorithm (ADA) presented in [29], which is a heuristic technique, to solve the bilinear subproblem of the CCGA rather than by using binary variables to model the deviations of the uncertain parameters and an exact linearization procedure [30]. The authors of [31] propose a two-stage ARO transmission and energy storage expansion planning model that includes the ramping limits of conventional generating units and the charging/discharging statuses of storage facilities, where the latter are modeled by using second-stage binary decision variables, which leads to the need to use the nested column-and-constraint generation algorithm (NCCGA) [32] rather than the CCGA. Note that the authors of [31] combine the NCCGA with the ADA to reduce the computational burden, but the attainment of the global optimal solution is not ensured. The two-stage ARO TNEP model presented in [33] includes a detailed representation of the operation of the power system as done in [31], but also modeling the commitment statuses of conventional generating units and the uncertainty in the peak power consumption of loads. The numerical results provided in [33] show that the consideration of the non-convex operational feasibility sets of storage facilities and conventional generating units increases the computational time of the static two-stage ARO TNEP problem from minutes to hours. The authors of [34] propose two exact acceleration techniques applied to the NCCGA in order to reduce the computational burden of the two-stage ARO TNEP problems when inter-temporal and non-convex operational feasibility sets are considered. Note that all works mentioned above ignore the multi-year nature of the expansion planning problems since a static approach is considered.

Conversely, a multi-year approach has been used in recent works, but at the expense of modeling neither inter-temporal nor non-convex operational feasibility sets and considering only one representative time period (RTP) associated with the peak power consumption of loads in most of the cases. The multi-year two-stage ARO TNEP problem is addressed in [14] considering annual evolution rates to model the changes of the forecast values and the maximum deviations of the uncertain parameters in each year of the planning horizon. A multi-year approach of the two-stage ARO generation and transmission network expansion planning problem is proposed in [15] where the dismantling of conventional and renewable generating units is modeled. The authors of [16] propose a multi-year two-stage ARO TNEP model in which a preventive  $n - K$  security criterion is used to identify the contingencies of transmission lines and generating units that maximize the operating costs. Moreover, the authors of [35] propose reducing the computational time of the multi-year two-stage ARO generation and transmission network expansion planning problem by applying Benders decomposition to the master problem of the CCGA.

The features of previous two-stage ARO expansion planning approaches are shown in Table 1, namely, the consideration of the operational variability of the weather-based renewable generation and the electrical demand, the presence of renewable generating units, the ramping limits and commitment statuses of conventional generating units, the presence and the charging/discharging statuses of storage facilities, and the possibility of building new facilities in each year of the planning horizon by considering a multi-year approach. Symbols ✓ and × are used to illustrate whether a particular feature has been

considered or not, respectively. Note that all the features shown in Table 1 have not simultaneously been considered in previous two-stage ARO expansion planning approaches.

It is worth mentioning that previous works that use the NCCGA to solve two-stage ARO expansion planning problems, such as [16,31], do not consider approaches as complex as the one presented in this work in order to avoid computational issues. For instance, the authors of [16] do not model the operational variability of the power system, the ramping limits of conventional generating units, and the presence of storage facilities. Moreover, the authors of [31] consider a static approach rather than a multi-year formulation and they do not model the commitment statuses of conventional generating units. This highlights the need to combine the NCCGA with acceleration techniques in order to address more complex approaches as that presented in this work.

### 1.3. Contributions

Given this context, the contributions of this paper are twofold:

1. The formulation and solution procedure of a multi-year two-stage ARO TNEP problem with high penetration of renewable generation that jointly models the operational variability and the inter-temporal and non-convex operational feasibility sets of storage facilities and conventional generating units. The simultaneous consideration of all these features entails a contribution with respect to previous two-stage ARO TNEP approaches, as shown in Table 1. Note that previous works that model the multi-year nature of the problem usually neglect the operational variability, the ramping limits of conventional generating units, and the presence of storage facilities, among other features, in order to prevent computationally intractable problems. Despite the high complexity of the problem, the global optimal solution is attained in a finite number of steps by combining the NCCGA with two exact acceleration techniques.
2. The comparison of the proposed approach with simpler models. First, the multi-year two-stage ARO TNEP approach is compared with the sequential static and static models. Second, the proposed framework is compared with a relaxed approach in which the detailed operation of power systems is ignored, namely, the ramping limits and commitment statuses of conventional generating units, as well as the charging/discharging statuses of storage facilities.

### 1.4. Organization of paper

The remainder of this paper is organized as follows. Section 2 provides the description of the multi-year ARO TNEP problem, including its detailed notation and formulation. Section 3 describes the solution procedure employed for the problem, in which the NCCGA is combined with two exact acceleration techniques. Section 4 presents the numerical results of two case studies. Section 5 shows the conclusions of this paper, and finally, Appendix describes the changes to be made in the formulation of the multi-year two-stage ARO TNEP problem described in Section 2 when static and sequential static approaches are considered.

## 2. Description of the problem

The multi-year two-stage ARO TNEP problem is solved by the TSO in order to minimize the total worst-case cost by identifying which candidate transmission lines should be built and the optimal timing of these investment decisions. We consider a two-stage model in which the worst-case uncertainty realization of the peak power consumption of loads, as well as of the capacity and marginal production cost of generating units is modeled by applying ARO. This means that the multi-year two-stage ARO TNEP problem follows the following decision sequence:

**Table 1**  
Comparison of previous two-stage ARO expansion planning approaches.

Reference	Operational variability	Renewable generation	Ramping limits	Commitment statuses	Storage facilities	Charging/Discharging statuses	Multi-year approach
[14]	×	×	×	×	×	×	✓
[15]	×	✓	×	×	×	×	✓
[16]	×	✓	×	✓	×	×	✓
[17,19]	✓	✓	×	×	×	×	×
[18]	✓	✓	✓	×	✓	✓*	×
[21,23]	×	✓	×	×	×	×	×
[26]	×	×	×	×	×	×	×
[31]	✓	✓	✓	×	✓	✓	×
[33]	✓	✓	✓	✓	✓	✓	×
[35]	✓	✓	✓	×	✓	×	✓
This paper	✓	✓	✓	✓	✓	✓	✓

\*The non-convex operational feasibility sets of storage facilities are not modeled correctly since first-stage variables are used rather than second-stage variables.

1. The TSO determines which reinforcements should be made in the transmission network in each year of the planning horizon in order to minimize the total cost.
2. The worst-case uncertainty realization that maximizes the operating costs occurs.
3. The TSO takes corrective actions associated with the operation of the power system in order to minimize the operating costs.

We assume that the capacity of conventional and renewable generating units may undergo decreases in their forecast values, while the marginal production cost of conventional generating units and the peak power consumption of loads may undergo increases in their forecast values. With regard to the operational variability of the electrical demand and the weather-based renewable production, a set of RDs is considered. The operation of storage facilities can, therefore, be included in the formulation of the problem since the chronological sequence of the RTPs in each representative day (RD) is maintained. Furthermore, particular attention is paid to the operational flexibility of conventional generating units and the operation of storage facilities, namely, the ramping limits and commitment statuses of the former and the non-convex operational feasibility sets of the latter. Note that the multi-year two-stage approach considered in this work is a simplification of the true dynamic multi-stage ARO TNEP problem since we assume that the expansion decisions throughout the entire planning horizon are determined at the first stage of the problem. This simplification is common in the technical literature [14–16,35] and is considered to reduce the complexity of the solution procedure. The next subsections describe the notation and formulation of the multi-year two-stage ARO TNEP problem.

## 2.1. Notation

A subscript  $y/t/h$  in the symbols below denotes their values in the  $y$ th year/ $t$ th RD/ $h$ th RTP.

### 2.1.1. Indexes and sets

$v, k$  Iteration of the inner loop

$\Omega^D$  Set of loads indexed by  $d$ .

$\Omega_n^D$  Set of loads connected to bus  $n$ .

$\Omega^G$  Set of conventional generating units indexed by  $g$ .

$\Omega_n^G$  Set of conventional generating units connected to bus  $n$ .

$\Omega^H$  Set of RTPs indexed by  $h$ .

$\Omega^L$  Set of transmission lines indexed by  $\ell$ .

$\Omega^{L+}$  Set of candidate transmission lines.

$\Omega^N$  Set of buses indexed by  $n$ .

$\Omega^R$  Set of renewable generating units indexed by  $r$ .

$\Omega^{R,S}$  Set of solar-power units.

$\Omega^{R,W}$  Set of wind-power units.

$\Omega_n^R$  Set of renewable generating units connected to bus  $n$ .

$\Omega^S$  Set of storage facilities indexed by  $s$ .

$\Omega_n^S$  Set of storage facilities connected to bus  $n$ .

$\Omega^T$  Set of RDs indexed by  $t$ .

$\Omega^Y$  Set of years indexed by  $y$ .

$i, j$  Iteration of the outer loop.

$n(d)$  Bus location of load  $d$ .

$n(g)$  Bus location of conventional generating unit  $g$ .

$n(r)$  Bus location of renewable generating unit  $r$ .

$n(s)$  Bus location of storage facility  $s$ .

$o$  Iteration of the ADA.

$r^I$  Iteration of the relaxed inner loop.

$r^O$  Iteration of the relaxed outer loop.

$RE(\ell)$  Receiving bus of transmission line  $\ell$ .

$SE(\ell)$  Sending bus of transmission line  $\ell$ .

### 2.1.2. Parameters

$\gamma_{dyth}^D$  Demand factor of load  $d$ .

$\gamma_{ryth}^R$  Capacity factor of renewable generating unit  $r$ .

$I^D$  Uncertainty budget that represents the maximum number of loads that can simultaneously undergo increases in their forecast peak power consumption.

$I^{G,C}$  Uncertainty budget that represents the maximum number of conventional generating units that can simultaneously undergo increases in their forecast marginal production costs.

$I^{G,P}$  Uncertainty budget that represents the maximum number of conventional generating units that can simultaneously undergo decreases in their forecast capacities.

$\Gamma^{R,S}$	Uncertainty budget that represents the maximum number of solar-power units that can simultaneously undergo decreases in their forecast capacities.	$\bar{P}_g^G$	Forecast capacity of conventional generating unit $g$ in year 1.
$\Gamma^{R,W}$	Uncertainty budget that represents the maximum number of wind-power units that can simultaneously undergo decreases in their forecast capacities.	$\hat{P}_g^G$	Maximum deviation from the forecast capacity of conventional generating unit $g$ in year 1.
$\tilde{\zeta}_d^D$	Annual evolution rate of the forecast peak power consumption of load $d$ .	$\bar{P}_\ell^L$	Power flow capacity of transmission line $\ell$ .
$\hat{\zeta}_d^D$	Annual evolution rate of the maximum deviation from the forecast peak power consumption of load $d$ .	$\bar{P}_r^R$	Forecast capacity of renewable generating unit $r$ in year 1.
$\tilde{\zeta}_g^{G,C}$	Annual evolution rate of the forecast marginal production cost of conventional generating unit $g$ .	$\hat{P}_r^R$	Maximum deviation from the forecast capacity of renewable generating unit $r$ in year 1.
$\hat{\zeta}_g^{G,C}$	Annual evolution rate of the maximum deviation from the forecast marginal production cost of conventional generating unit $g$ .	$\bar{P}_s^{S,C}$	Charging power capacity of storage facility $s$ .
$\tilde{\zeta}_g^{G,P}$	Annual evolution rate of the forecast capacity of conventional generating unit $g$ .	$\bar{P}_s^{S,D}$	Discharging power capacity of storage facility $s$ .
$\hat{\zeta}_g^{G,P}$	Annual evolution rate of the maximum deviation from the forecast capacity of conventional generating unit $g$ .	$R_g^{G,D}$	Ramp-down limit of conventional generating unit $g$ .
$\tilde{\zeta}_r^R$	Annual evolution rate of the forecast capacity of renewable generating unit $r$ .	$R_g^{G,U}$	Ramp-up limit of conventional generating unit $g$ .
$\hat{\zeta}_r^R$	Annual evolution rate of the maximum deviation from the forecast capacity of renewable generating unit $r$ .	$X_\ell$	Reactance of transmission line $\ell$ .
$\eta_s^{S,C}$	Charging efficiency of storage facility $s$ .	<b>2.1.3. Variables</b>	
$\eta_s^{S,D}$	Discharging efficiency of storage facility $s$ .	$\theta_{nyth}$	Voltage angle at bus $n$ .
$\kappa$	Discount rate.	$\xi_y$	Auxiliary variable of the inner-loop master problem.
$\sigma_{yt}$	Weight of RD $t$ .	$\xi_y^P$	Auxiliary variable of the first problem solved at each iteration of the ADA when it is applied to the inner-loop master problem.
$\tau_{yth}$	Duration of RTP $h$ of RD $t$ .	$\xi_y^Q$	Auxiliary variable of the second problem solved at each iteration of the ADA when it is applied to the inner-loop master problem.
$\bar{C}_g^G$	Forecast marginal production cost of conventional generating unit $g$ in year 1.	$\rho_y$	Auxiliary variable of the outer-loop master problem.
$\hat{C}_g^G$	Maximum deviation from the forecast marginal production cost of conventional generating unit $g$ in year 1.	$a_{dy}^D$	Continuous variable associated with the deviation that the peak power consumption of load $d$ can experience from its forecast value in year $y$ .
$C_d^{LS}$	Load-shedding cost coefficient of load $d$ .	$a_{gy}^{G,C}$	Continuous variable associated with the deviation that the marginal production cost of conventional generating unit $g$ can experience from its forecast value in year $y$ .
$C_r^R$	Spillage cost coefficient of renewable generating unit $r$ .	$a_{gy}^{G,P}$	Continuous variable associated with the deviation that the capacity of conventional generating unit $g$ can experience from its forecast value in year $y$ .
$E_{syrt0}^S$	Energy initially stored of storage facility $s$ .	$a_{ry}^R$	Continuous variable associated with the deviation that the capacity of renewable generating unit $r$ can experience from its forecast value in year $y$ .
$\underline{E}_s^S$	Minimum energy level of storage facility $s$ .	$c_{gy}^G$	Worst-case realization of the marginal production cost of conventional generating unit $g$ .
$\bar{E}_s^S$	Maximum energy level of storage facility $s$ .	$c_y^O$	Operating costs.
$H$	Number of RTPs of each RD.	$c_y^{O,WC}$	Worst-case operating costs.
$I_\ell^L$	Investment cost coefficient of candidate transmission line $\ell$ .	$e_{syth}^S$	Energy stored in storage facility $s$ .
$\bar{I}^T$	Investment budget.	$\bar{p}_{dy}^D$	Worst-case realization of the peak power consumption of load $d$ .
$\bar{P}_d^D$	Forecast peak power consumption of load $d$ in year 1.	$p_{gyth}^G$	Power produced by conventional generating unit $g$ .
$\hat{P}_d^D$	Maximum deviation from the forecast peak power consumption of load $d$ in year 1.	$\bar{p}_{gy}^G$	Worst-case realization of the capacity of conventional generating unit $g$ .
$\underline{P}_g^G$	Minimum production level of conventional generating unit $g$ .	$p_{\ell yth}^L$	Power flow through transmission line $\ell$ .



$p_{dyth}^{LS}$	Unserved demand of load $d$ .
$p_{ryth}^R$	Power produced by renewable generating unit $r$ .
$\bar{p}_{ry}^R$	Worst-case realization of the capacity of renewable generating unit $r$ .
$p_{syth}^{S,C}$	Charging power of storage facility $s$ .
$p_{syth}^{S,D}$	Discharging power of storage facility $s$ .
$u_{gyth}^G$	Binary variable used to model the commitment status of conventional generating unit $g$ .
$u_{syth}^S$	Binary variable used to avoid the simultaneous charging and discharging of storage facility $s$ .
$v_{\ell y}^L$	Binary variable that is equal to 1 if candidate transmission line $\ell$ is built in year $y$ , which is otherwise 0.
$\bar{v}_{\ell y}^L$	Binary variable that is equal to 1 if candidate transmission line $\ell$ is built in year $y$ or in previous years, which is otherwise 0.
$z_{dy}^D$	Binary variable that is equal to 1 if the worst-case realization of the peak power consumption of load $d$ is equal to its upper bound, which is otherwise 0.
$z_{gy}^{G,C}$	Binary variable that is equal to 1 if the worst-case realization of the marginal production cost of conventional generating unit $g$ is equal to its upper bound, which is otherwise 0.
$z_{gy}^{G,P}$	Binary variable that is equal to 1 if the worst-case realization of the capacity of conventional generating unit $g$ is equal to its lower bound, which is otherwise 0.
$z_{ry}^R$	Binary variable that is equal to 1 if the worst-case realization of the capacity of renewable generating unit $r$ is equal to its lower bound, which is otherwise 0.

#### 2.1.4. Dual variables

$\lambda_{nyth}^N$	Dual variable associated with the power balance equation at bus $n$ .
$\bar{\mu}_{dyth}^D$	Dual variable associated with the constraint imposing the upper bound for the unserved demand of load $d$ .
$\bar{\mu}_{gyth}^G$	Dual variable associated with the constraint imposing the lower bound for the power produced by conventional generating unit $g$ .
$\bar{\mu}_{gyth}^G$	Dual variable associated with the constraint imposing the upper bound for the power produced by conventional generating unit $g$ .
$\bar{\mu}_{gyth}^{G,D}$	Dual variable associated with the constraint imposing the ramp-down limit of conventional generating unit $g$ , being $h$ greater than 1.
$\bar{\mu}_{gyth}^{G,U}$	Dual variable associated with the constraint imposing the ramp-up limit of conventional generating unit $g$ , being $h$ greater than 1.
$\mu_{\ell yth}^L$	Dual variable associated with the power flow through existing transmission line $\ell$ .
$\mu_{\ell yth}^{L+}$	Dual variable associated with the power flow through candidate transmission line $\ell$ .
$\bar{\mu}_{\ell yth}^L$	Dual variable associated with the constraint imposing the lower bound for the power flow through transmission line $\ell$ .

$\bar{\mu}_{\ell yth}^L$	Dual variable associated with the constraint imposing the upper bound for the power flow through transmission line $\ell$ .
$\bar{\mu}_{ryth}^R$	Dual variable associated with the constraint imposing the upper bound for the power produced by renewable generating unit $r$ .
$\mu_{syth}^S$	Dual variable associated with the energy stored in storage facility $s$ , being $h$ greater than 1.
$\bar{\mu}_{syth}^S$	Dual variable associated with the constraint imposing the lower bound for the energy stored in storage facility $s$ .
$\bar{\mu}_{syth}^S$	Dual variable associated with the constraint imposing the upper bound for the energy stored in storage facility $s$ .
$\bar{\mu}_{syth}^{S,C}$	Dual variable associated with the constraint imposing the upper bound for the charging power of storage facility $s$ .
$\bar{\mu}_{syth}^{S,D}$	Dual variable associated with the constraint imposing the upper bound for the discharging power of storage facility $s$ .
$\phi_{syth}^S$	Dual variable associated with the energy stored in storage facility $s$ at the first RTP of RD $t$ .
$\bar{\phi}_{syth}^S$	Dual variable associated with the constraint imposing the lower bound for the energy stored in storage facility $s$ at the last RTP of RD $t$ .
$\varphi_{nyth}^N$	Dual variable associated with the definition of the reference bus $n$ .

#### 2.2. Formulation

The three-level formulation of the multi-year two-stage ARO model is provided below:

$$\min_{\phi^{UL}} \sum_{y \in \Omega^Y} \frac{1}{(1 + \kappa)^{y-1}} \left( \frac{c_y^{O,WC}}{1 + \kappa} + \sum_{\ell \in \Omega^{L+}} I_{\ell}^L v_{\ell y}^L \right) \quad (1a)$$

subject to:

$$v_{\ell y}^L \in \{0, 1\}; \quad \forall \ell \in \Omega^{L+}, \forall y \in \Omega^Y, \quad (1b)$$

$$\sum_{\ell \in \Omega^{L+}} \sum_{y \in \Omega^Y} \frac{1}{(1 + \kappa)^{y-1}} I_{\ell}^L v_{\ell y}^L \leq \bar{I}^T, \quad (1c)$$

$$\sum_{y \in \Omega^Y} v_{\ell y}^L \leq 1; \quad \forall \ell \in \Omega^{L+}, \quad (1d)$$

$$\bar{v}_{\ell y}^L = \sum_{\bar{y}=1}^{\bar{y}=y} v_{\ell \bar{y}}^L; \quad \forall \ell \in \Omega^{L+}, \forall y \in \Omega^Y, \quad (1e)$$

$$c_y^{O,WC} = \begin{cases} \max_{\phi^{ML}} c_y^O \end{cases} \quad (2a)$$

subject to:

$$c_{gy}^G = \bar{c}_g^G \left( 1 + \bar{\zeta}_g^{G,C} \right)^{y-1} + \hat{c}_g^G \left( 1 + \hat{\zeta}_g^{G,C} \right)^{y-1} z_{gy}^{G,C}; \quad \forall g \in \Omega^G, \quad (2b)$$

$$\bar{p}_{dy}^D = \bar{p}_d^D \left( 1 + \bar{\zeta}_d^D \right)^{y-1} + \hat{p}_d^D \left( 1 + \hat{\zeta}_d^D \right)^{y-1} z_{dy}^D; \quad \forall d \in \Omega^D, \quad (2c)$$

$$\bar{p}_{gy}^G = \bar{p}_g^G \left( 1 - \bar{\zeta}_g^{G,P} \right)^{y-1} - \hat{p}_g^G \left( 1 + \hat{\zeta}_g^{G,P} \right)^{y-1} z_{gy}^{G,P}; \quad \forall g \in \Omega^G, \quad (2d)$$

$$\bar{p}_{ry}^R = \bar{p}_r^R \left( 1 + \bar{\zeta}_r^R \right)^{y-1} - \hat{p}_r^R \left( 1 + \hat{\zeta}_r^R \right)^{y-1} z_{ry}^R; \quad \forall r \in \Omega^R, \quad (2e)$$

$$z_{gy}^{G,C} \in \{0, 1\}; \quad \forall g \in \Omega^G, \quad (2f)$$

$$z_{dy}^D \in \{0, 1\}; \quad \forall d \in \Omega^D, \quad (2g)$$

$$z_{gy}^{G,P} \in \{0, 1\}; \quad \forall g \in \Omega^G, \quad (2h)$$

$$z_{ry}^R \in \{0, 1\}; \quad \forall r \in \Omega^R, \quad (2i)$$

$$\sum_{g \in \Omega^G} z_{gy}^{G,C} \leq I^{G,C}, \quad (2j)$$

$$\sum_{d \in \Omega^D} z_{dy}^D \leq I^D, \quad (2k)$$

$$\sum_{g \in \Omega^G} z_{gy}^{G,P} \leq I^{G,P}, \quad (2l)$$

$$\sum_{r \in \Omega^{R,S}} z_{ry}^{R,S} \leq I^{R,S}, \quad (2m)$$

$$\sum_{r \in \Omega^{R,W}} z_{ry}^{R,W} \leq I^{R,W}, \quad (2n)$$

$$c_y^O = \min_{\Phi^{LL}} \sum_{t \in \Omega^T} \sigma_{yt} \sum_{h \in \Omega^H} \tau_{yth} \left( \sum_{g \in \Omega^G} c_{gyt}^G p_{gyth}^G + \sum_{r \in \Omega^R} C_r^R (\gamma_{ryth}^R \bar{p}_{ry}^R - p_{ryth}^R) \right. \\ \left. + \sum_{d \in \Omega^D} C_d^{LS} p_{dyth}^{LS} \right) \quad (3a)$$

subject to:

$$\sum_{g \in \Omega_n^G} p_{gyth}^G + \sum_{r \in \Omega_n^R} p_{ryth}^R + \sum_{\ell \in \Omega^L | RE(\ell)=n} p_{\ell yth}^L - \sum_{\ell \in \Omega^L | SE(\ell)=n} p_{\ell yth}^L \\ + \sum_{s \in \Omega_n^S} (p_{syth}^{S,D} - p_{syth}^{S,C}) = \sum_{d \in \Omega_n^D} (\gamma_{dyth}^D \bar{p}_{dy}^D - p_{dyth}^{LS}) : \lambda_{nyth}^N; \\ \forall n \in \Omega^N, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3b)$$

$$p_{\ell yth}^L = \frac{1}{X_\ell} (\theta_{SE(\ell)yth} - \theta_{RE(\ell)yth}) : \mu_{\ell yth}^L; \quad \forall \ell \in \Omega^L \setminus \Omega^{L+}, \\ \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3c)$$

$$p_{\ell yth}^L = \frac{\bar{p}_{\ell y}^L}{X_\ell} (\theta_{SE(\ell)yth} - \theta_{RE(\ell)yth}) : \mu_{\ell yth}^{L+}; \quad \forall \ell \in \Omega^{L+}, \forall t \in \Omega^T, \\ \forall h \in \Omega^H, \quad (3d)$$

$$-\bar{p}_\ell^L \leq p_{\ell yth}^L \leq \bar{p}_\ell^L : \underline{\mu}_{\ell yth}^L, \bar{\mu}_{\ell yth}^L; \quad \forall \ell \in \Omega^L, \forall t \in \Omega^T, \\ \forall h \in \Omega^H, \quad (3e)$$

$$e_{syth}^S = E_{syth}^S + \left( p_{syth}^{S,C} \eta_s^{S,C} - \frac{p_{syth}^{S,D}}{\eta_s^{S,D}} \right) \tau_{syth} : \phi_{syth}^S; \quad \forall s \in \Omega^S, \\ \forall t \in \Omega^T, \quad (3f)$$

$$e_{syth}^S = e_{syth-1}^S + \left( p_{syth}^{S,C} \eta_s^{S,C} - \frac{p_{syth}^{S,D}}{\eta_s^{S,D}} \right) \tau_{syth} : \mu_{syth}^S; \quad \forall s \in \Omega^S, \\ \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \quad (3g)$$

$$E_{syth}^S \leq e_{syth}^S : \phi_{syth}^S; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (3h)$$

$$E_s^S \leq e_{syth}^S \leq \bar{E}_s^S : \underline{\mu}_{syth}^S, \bar{\mu}_{syth}^S; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3i)$$

$$u_{syth}^S \in \{0, 1\}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3j)$$

$$0 \leq p_{syth}^{S,C} \leq u_{syth}^S \bar{p}_s^{S,C} : \bar{\mu}_{syth}^{S,C}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3k)$$

$$0 \leq p_{syth}^{S,D} \leq (1 - u_{syth}^S) \bar{p}_s^{S,D} : \bar{\mu}_{syth}^{S,D}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \\ \forall h \in \Omega^H, \quad (3l)$$

$$0 \leq p_{dyth}^{LS} \leq \gamma_{dyth}^D \bar{p}_{dy}^D : \bar{\mu}_{dyth}^D; \quad \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3m)$$

$$u_{gyth}^G \in \{0, 1\}; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3n)$$

$$u_{gyth}^G p_{gyth}^G \leq p_{gyth}^G \leq u_{gyth}^G \bar{p}_{gy}^G : \underline{\mu}_{gyth}^G, \bar{\mu}_{gyth}^G; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \\ \forall h \in \Omega^H, \quad (3o)$$

$$-R_g^{G,D} \leq p_{gyth}^G - p_{gyth-1}^G \leq R_g^{G,U} : \underline{\mu}_{gyth}^{G,D}, \bar{\mu}_{gyth}^{G,U}; \quad \forall g \in \Omega^G, \\ \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \quad (3p)$$

$$0 \leq p_{ryth}^R \leq \gamma_{ryth}^R \bar{p}_{ry}^R : \bar{\mu}_{ryth}^R; \quad \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (3q)$$

$$\theta_{nyth} = 0 : \varphi_{nyth}^N; \quad n : ref., \forall t \in \Omega^T, \forall h \in \Omega^H \}, \forall y \in \Omega^Y, \quad (3r)$$

where set  $\Phi^{UL} = \{c_y^{O,WC}, \forall y \in \Omega^Y; v_{\ell y}^L, \bar{v}_{\ell y}^L, \forall \ell \in \Omega^{L+}, \forall y \in \Omega^Y\}$  represents first-stage decision variables, variables in set  $\Phi^{ML} = \{c_y^O, \forall y \in \Omega^Y; \bar{p}_{dy}^D, z_{dy}^D, \forall d \in \Omega^D, \forall y \in \Omega^Y; c_{gy}^G, \bar{p}_{gy}^G, z_{gy}^G, z_{gy}^{G,P}, \forall g \in \Omega^G, \forall y \in \Omega^Y; \bar{p}_{ry}^R, z_{ry}^R, \forall r \in \Omega^R, \forall y \in \Omega^Y\}$  comprise the worst-case uncertainty realization, and set  $\Phi^{LL} = \{p_{gyth}^G, u_{gyth}^G, \forall g \in \Omega^G, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H; p_{ryth}^R, \forall r \in \Omega^R, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H; p_{dyth}^{LS}, \forall d \in \Omega^D, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H; p_{\ell yth}^L, \forall \ell \in \Omega^L, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H; e_{syth}^S, p_{syth}^{S,C}, p_{syth}^{S,D}, u_{syth}^S, \forall s \in \Omega^S, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H; \theta_{nyth}, \forall n \in \Omega^N, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H\}$  includes the second-stage operating decision variables.

The upper-level problem (1) minimizes the sum of the worst-case operating and investment costs (1a). We assume that the former costs are calculated throughout each year, while the latter are computed at the beginning of each year since expansion decisions are made at that time, as described in [15]. Hence, the worst-case operating and investment costs in year  $y$  are multiplied by  $\frac{1}{(1+\kappa)^y}$  and  $\frac{1}{(1+\kappa)^{y-1}}$ , respectively, to compute their value at the time of determining the expansion decisions. The binary nature of investment-decision variables  $v_{\ell y}^L$  is defined in constraints (1b). An investment budget is used in constraint (1c) to limit the investment costs. The possibility of building each candidate transmission line only once throughout the planning horizon is imposed in constraints (1d). The building status of a candidate transmission line  $\bar{v}_{\ell y}^L$  is established in constraints (1e).

Additionally, the middle-level problem (2) maximizes the worst-case operating costs for year  $y$  (2a) and given investment decisions identified by the upper-level problem (1). Eqs. (2b)–(2e) define the uncertain variables, namely, the marginal production cost of conventional generating units, the peak power consumption of loads, and the capacity of conventional and renewable generating units, respectively. The forecast values and the maximum deviations of these variables evolve throughout the planning horizon based on annual evolution rates, as described in [14]. Note that this formulation allows that the forecast values and the maximum deviations may evolve by following growth or downward tendencies because the annual evolution rates can be positive or negative. Constraints (2f)–(2i) define the binary nature of the variables used to represent whether uncertain parameters undergo deviations from their forecast values or not. Constraints (2j)–(2n) limit the number of units in each set of uncertain variables that may undergo deviations from their forecast values in each year by using uncertainty budgets. It should be stressed that we use a cardinality-constrained uncertainty set since it allows obtaining the global optimal solution of the multi-year two-stage ARO TNEP problem when the two lowermost max–min optimization levels are recast as an equivalent single-level optimization problem by using the Lagrangian duality theory and an exact linearization technique, as described in Section 3. Note that the Lagrangian dual problem of the lower-level problem is formulated for given values of the second-stage binary decision variables, i.e., the duality theory is applied to a linear programming problem.

With regard to the lower-level problem (3), the operating costs are minimized for year  $y$  (3a) subject to the expansion decisions and the uncertainty realization determined by the upper- and middle-level problems, respectively. The operating costs for year  $y$  are computed as the sum of the production costs of conventional generating units, the spillage costs of renewable generating units, and the unserved demand costs of loads. Eqs. (3b) define the power balance at each bus. A lossless DC model is used in Eqs. (3c) and (3d) to define the power flows through existing and candidate transmission lines, respectively, which are limited in constraints (3e). Eqs. (3f) and (3g) define the energy stored in storage facilities for the first RTP and the rest of RTPs of each RD, respectively. Constraints (3h) ensure that the energy stored in storage facilities at the end of each RD is greater than or equal to their energy initially stored in the RD. Constraints (3i) impose minimum and maximum bounds on the energy stored. Constraints (3j) define the binary nature of the variables used to avoid the simultaneous charging and discharging of storage facilities. Constraints (3k) and (3l) impose

limits on the charging and discharging power levels of storage facilities, respectively. Constraints (3m) establish limits on the unserved demand of loads. Constraints (3n) define the binary variables used to model the commitment statuses of conventional generating units. Constraints (3o) and (3p) impose bounds on the production of conventional generating units by using capacity and ramping limits, respectively. Constraints (3q) impose limits on the power produced by renewable generating units. Finally, Eqs. (3r) establish the voltage angle at the reference bus. Note that constraints (3b)–(3r), with the exception of constraints (3j) and (3n), are followed by a colon and the corresponding dual variables.

### 3. Solution procedure

We solve the multi-year two-stage ARO TNEP problem by combining the NCCGA [32] with two exact acceleration techniques [34].

The NCCGA is an exact solution technique to solve two-stage ARO problems in which the set of lower-level variables comprises continuous and integer recourse variables, i.e., a mixed-integer recourse problem is considered.

The NCCGA, which ensures that the global optimal solution is obtained for problem (1)–(3) [32], is based on applying a hierarchical structure of two loops, each of which is composed of a subproblem and a master problem. Note that cutting planes are iteratively included at the outer- and inner-loop master problems of the NCCGA until the convergence of both loops is attained. This may lead to the use of a large number of variables and constraints and, therefore, computationally intractable problems. Thus, we combine the NCCGA with two exact acceleration techniques, namely, the relaxation of the master problems and the ADA-based initialization of the inner loop.

The formulations of the subproblem and master problems of the NCCGA combined with these two acceleration techniques are described in the following subsections.

#### 3.1. Outer-loop master problem

The outer-loop master problem is modeled at outer-loop iteration  $j$  and relaxed outer-loop iteration  $r^0$  as follows:

$$\min_{\Phi^{\text{OLMP}}} \sum_{y \in \Omega^Y} \frac{1}{(1 + \kappa)^{y-1}} \left( \frac{\rho_y}{1 + \kappa} + \sum_{\ell \in \Omega^{L+}} I_{\ell}^L v_{\ell y}^L \right) \quad (4a)$$

subject to:

$$\text{Constraints (1b)–(1e),} \quad (4b)$$

$$\left\{ \begin{aligned} \rho_y &\geq \sum_{i \in \Omega^T} \sigma_{yt} \sum_{h \in \Omega^H} \tau_{yth} \left( \sum_{g \in \Omega^G} c_{gy}^{G(i)} p_{gyth}^G + \sum_{r \in \Omega^R} C_r^R \left( \gamma_{ryth}^R \bar{p}_{ry}^{R(i)} - p_{ryth}^R \right) \right. \\ &\quad \left. + \sum_{d \in \Omega^D} C_d^{LS} p_{dyth}^{LS} \right), \end{aligned} \right. \quad (4c)$$

$$\begin{aligned} &\sum_{g \in \Omega_n^G} p_{gyth}^G + \sum_{r \in \Omega_n^R} p_{ryth}^R + \sum_{\ell \in \Omega_n^{L-} | RE(\ell)=n} p_{\ell yth}^L - \sum_{\ell \in \Omega_n^{L-} | SE(\ell)=n} p_{\ell yth}^L \\ &+ \sum_{s \in \Omega_n^S} (p_{syth}^{S,D} - p_{syth}^{S,C}) = \sum_{d \in \Omega_n^D} (\gamma_{dyth}^D \bar{p}_{dy}^{D(i)} - p_{dyth}^{LS}); \quad \forall n \in \Omega^N, \\ &\forall t \in \Omega^T, \forall h \in \Omega^H, \end{aligned} \quad (4d)$$

$$p_{\ell yth}^L = \frac{1}{X_{\ell}} (\theta_{SE(\ell)yth} - \theta_{RE(\ell)yth}); \quad \forall \ell \in \Omega^L \setminus \Omega^{L+}, \forall t \in \Omega^T, \quad (4e)$$

$$p_{\ell yth}^L = \frac{\bar{v}_{\ell y}^L}{X_{\ell}} (\theta_{SE(\ell)yth} - \theta_{RE(\ell)yth}); \quad \forall \ell \in \Omega^{L+}, \forall t \in \Omega^T, \quad (4f)$$

$$-\bar{p}_{\ell}^L \leq p_{\ell yth}^L \leq \bar{p}_{\ell}^L; \quad \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4g)$$

$$e_{syth}^S = E_{syth}^S + \left( p_{syth}^{S,C} \eta_s^{S,C} - \frac{p_{syth}^{S,D}}{\eta_s^{S,D}} \right) \tau_{yth}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (4h)$$

$$e_{syth}^S = e_{syth-1}^S + \left( p_{syth}^{S,C} \eta_s^{S,C} - \frac{p_{syth}^{S,D}}{\eta_s^{S,D}} \right) \tau_{yth}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (4i)$$

$$\underline{E}_{syth}^S \leq e_{syth}^S; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (4j)$$

$$\underline{E}_s^S \leq e_{syth}^S \leq \bar{E}_s^S; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4k)$$

$$u_{syth}^S \in \{0, 1\}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4l)$$

$$0 \leq p_{syth}^{S,C} \leq u_{syth}^S \bar{p}_s^{S,C}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4m)$$

$$0 \leq p_{syth}^{S,D} \leq (1 - u_{syth}^S) \bar{p}_s^{S,D}; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4n)$$

$$0 \leq p_{dyth}^{LS} \leq \gamma_{dyth}^D \bar{p}_{dy}^{D(i)}; \quad \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4o)$$

$$u_{gyth}^G \in \{0, 1\}; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4p)$$

$$\begin{aligned} &u_{gyth}^G \bar{p}_g^G \leq p_{gyth}^G \leq u_{gyth}^G \bar{p}_{gy}^{G(i)}; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \\ &-R_g^{G,D} \leq p_{gyth}^G - p_{gyth-1}^G \leq R_g^{G,U}; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \end{aligned} \quad (4q)$$

$$\forall h \in \Omega^H \setminus \{1\}, \quad (4r)$$

$$0 \leq p_{ryth}^R \leq \gamma_{ryth}^R \bar{p}_{ry}^{R(i)}; \quad \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (4s)$$

$$\begin{aligned} &\theta_{nyth} = 0; \quad n : ref., \forall t \in \Omega^T, \forall h \in \Omega^H \} \}, \forall y \in \Omega^Y, \\ &i = j - r^0 + 1, \dots, j, \end{aligned} \quad (4t)$$

where set  $\Phi^{\text{OLMP}} = \{\rho_y, \forall y \in \Omega^Y; v_{\ell y}^L, \bar{v}_{\ell y}^L, \forall \ell \in \Omega^{L+}, \forall y \in \Omega^Y; p_{gyth}^G, u_{gyth}^G, \forall g \in \Omega^G, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j; p_{ryth}^R, \forall r \in \Omega^R, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j; p_{dyth}^{LS}, \forall d \in \Omega^D, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j; p_{\ell yth}^L, \forall \ell \in \Omega^L, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j; e_{syth}^S, p_{syth}^{S,C}, p_{syth}^{S,D}, u_{syth}^S, \forall s \in \Omega^S, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j; \theta_{nyth}, \forall n \in \Omega^N, \forall y \in \Omega^Y, \forall t \in \Omega^T, \forall h \in \Omega^H, i = j - r^0 + 1, \dots, j\}$  includes the optimization variables of problem (4). Note that second-stage operating decision variables, such as  $p_{gyth}^G$ , include a subscript  $i$  since they are related to the uncertainty realizations  $c_{gy}^{G(i)}, \bar{p}_{dy}^{D(i)}, \bar{p}_{gy}^{G(i)}$ , and  $\bar{p}_{ry}^{R(i)}$ , where the values of the middle-level variables are determined by the outer-loop subproblem at previous outer-loop iterations. It is worth mentioning that the use of the conventional NCCGA implies that constraints (4c)–(4t) are evaluated for  $i = 1, \dots, j$  rather than for  $i = j - r^0 + 1, \dots, j$ .

The outer-loop master problem (4) is a relaxed version of the three-level problem (1)–(3) in which the first-stage decision variables are determined and the recourse objective function value is approximated by using a set of cutting planes based on the primal information of the lower-level problem for the realizations of the uncertain variables identified by the outer-loop subproblem at previous outer-loop iterations. In order to improve the computational performance, a relaxation of the outer-loop master problem is applied. In particular, it is solved by considering only the constraints and variables associated with the latest uncertainty realization determined by the outer-loop subproblem to speed up its solution procedure. Then, more cutting planes related to other uncertainty realizations previously identified by the outer-loop subproblem are added to the relaxed outer-loop master problem if its optimal objective function value does not increase with respect to its value in the previous outer-loop iteration. If  $j = 3$ , for instance, the first time that the relaxed outer-loop master problem is solved in outer-loop iteration  $j$  we set  $r^0$  to 1, which means that constraints (4c)–(4t) are evaluated only for  $i = 3$ . If the optimal objective function value of the relaxed outer-loop master problem does not increase with respect to its value in the previous outer-loop iteration, then we increase the value of  $r^0$  by one ( $r^0 = 2$ ) and the relaxed outer-loop master problem is solved by considering that constraints (4c)–(4t) are evaluated for



$i = 2, 3$ . This solution procedure is repeated until the optimal objective function value of the outer-loop master problem increases with respect to its value in the previous outer-loop iteration or until  $r^O > j$ . The convergence to the global optimal solution in a finite number of steps is still ensured when this acceleration technique is used since the solution procedure of the relaxed outer-loop master problem is repeated if needed until all active cutting planes are considered.

The objective function (4a) is analogous to (1a), but the worst-case operating costs for year  $y$  are approximately represented through the term  $\rho_y$ . This approximation is modeled in constraints (4c) by imposing a lower bound for  $\rho_y$  defined by the worst-case operating costs related to the uncertainty realization identified at previous iterations of the outer loop. Constraints (4d)–(4t) are similar to constraints (3b)–(3r) of the lower level.

Problem (4) is a mixed-integer non-linear programming (MINLP) problem since non-linear terms  $\bar{v}_{\ell y}^L \theta_{nyth}$  in constraints (4f) involve the product of binary first-stage expansion-decisions variables and continuous second-stage operating decision variables. The disjunctive linearization proposed by the authors of [36] allows recasting problem (4) as a mixed-integer linear programming (MILP) problem, which can be solved by using solvers such as CPLEX [37].

Note that the lower bound of the outer loop  $LB^O$  is updated to the optimal objective function value of the outer-loop master problem.

### 3.2. Outer-loop subproblem

The outer-loop subproblem comprises the two lowermost optimization levels for given values of the expansion-decision variables previously determined by the outer-loop master problem. Note that two modeling aspects considered make it possible to decompose the outer-loop subproblem by each year. On the one hand, we consider that the forecast value and the worst-case realization of the uncertain variables for a given year are independent of their values in the previous years, as shown in Eqs. (2b)–(2e). Note that this assumption has also been considered in previous multi-year two-stage ARO expansion planning problems [14–16,35] for the sake of simplicity. On the other, we model the inter-temporal operation of the power system in each year by using RDs that are independent of each other. Inter-day and inter-year constraints are, therefore, not considered. This means that we do not model, among other features, the evolution of the energy stored in storage facilities throughout the entire planning horizon.

The solution procedure of the outer-loop subproblem is attained by solving two problems that constitute the inner loop. The formulations of the inner-loop subproblem and inner-loop master problem of the NCCGA combined with the two acceleration techniques considered are described in the following subsections.

#### 3.2.1. Inner-loop master problem

The inner-loop master problem is formulated by recasting the two lowermost optimization levels as an equivalent single-level optimization problem by using the Lagrangian duality theory. In particular, the operating costs are approximately represented by using a set of cutting planes based on the lower-level dual objective function for given values of the binary recourse variables determined by the inner-loop subproblem at previous inner-loop iterations. In other words, the Lagrangian duality theory can be applied because the lower-level problem is formulated as a linear programming problem when the second-stage binary decision variables are fixed to the values previously obtained by solving the inner-loop subproblem.

The inner-loop master problem is formulated for given expansion-decision variables  $\bar{v}_{\ell y}^{L(j)}$  and binary operating decision variables  $\mu_{gyth}^{G(v)}$  and  $u_{syth}^{S(v)}$  for year  $y$  at outer-loop iteration  $j$ , iteration  $k$  of the inner loop and relaxed inner-loop iteration  $r^1$  as follows:

$$\max_{\phi_{ILMP}} \xi_y \quad (5a)$$

subject to:

$$\text{Constraints (2b)–(2n),} \quad (5b)$$

$$\begin{aligned} \left\{ \xi_y \leq \sum_{t \in \Omega^T} \left( \sum_{h \in \Omega^H} \left( \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^D \mu_{n(d)ythv}^N - \sum_{\ell \in \Omega^L} \bar{P}_{\ell}^L \left( \mu_{\ell ythv}^L + \bar{\mu}_{\ell ythv}^L \right) \right. \right. \right. \\ \left. \left. - \sum_{s \in \Omega^S} \left( u_{syth}^{S(v)} \bar{P}_s^{S,C-S,C} \mu_{sythv}^{S,C} + \left( 1 - u_{syth}^{S(v)} \right) \bar{P}_s^{S,D-S,D} \mu_{sythv}^{S,D} - \bar{E}_s^S \mu_{sythv}^S \right. \right. \right. \\ \left. \left. + \bar{E}_s^S \mu_{sythv}^S \right) + \sum_{g \in \Omega^G} u_{gyth}^{G(v)} \left( \bar{P}_g^{G,G} \mu_{gythv}^{G,G} - \bar{P}_{gy}^{G,G} \mu_{gythv}^{G,G} \right) \right. \\ \left. - \sum_{r \in \Omega^R} \gamma_{ryth}^R \bar{P}_{ry}^R \left( \bar{\mu}_{rythv}^R - \sigma_{yt} \tau_{ytr} C_r^R \right) - \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^D \mu_{dythv}^D \right) \\ \left. + \sum_{s \in \Omega^S} E_{syth}^S \left( \phi_{sythv}^S + \bar{\phi}_{sythv}^S \right) \right. \\ \left. - \sum_{h \in \Omega^H \setminus \{1\}} \sum_{g \in \Omega^G} \left( R_g^{G,D} \mu_{gythv}^{G,D} + R_g^{G,U} \bar{\mu}_{gythv}^{G,U} \right) \right); \end{aligned} \quad (5c)$$

$$\begin{aligned} \lambda_{n(g)yth1v}^N + \mu_{gyth1v}^G - \bar{\mu}_{gyth1v}^G - \mu_{gyth2v}^{G,D} + \bar{\mu}_{gyth2v}^{G,U} = \sigma_{yt} \tau_{ytr1} C_{gy}^G; \quad \forall g \in \Omega^G, \\ \forall t \in \Omega^T, \end{aligned} \quad (5d)$$

$$\begin{aligned} \lambda_{n(g)ythv}^N + \mu_{gythv}^G - \bar{\mu}_{gythv}^G + \mu_{gythv}^{G,D} - \mu_{gyth+1v}^{G,D} - \bar{\mu}_{gythv}^{G,U} + \bar{\mu}_{gyth+1v}^{G,U} \\ = \sigma_{yt} \tau_{ytr} C_{gy}^G; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1, H\}, \end{aligned} \quad (5e)$$

$$\begin{aligned} \lambda_{n(g)ythHv}^N + \mu_{gythHv}^G - \bar{\mu}_{gythHv}^G + \mu_{gythHv}^{G,D} - \bar{\mu}_{gythHv}^{G,U} = \sigma_{yt} \tau_{ytrH} C_{gy}^G; \quad \forall g \in \Omega^G, \\ \forall t \in \Omega^T, \end{aligned} \quad (5f)$$

$$\lambda_{n(d)ythv}^N - \bar{\mu}_{dythv}^D \leq \sigma_{yt} \tau_{ytr} C_d^{L,S}; \quad \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5g)$$

$$\lambda_{n(r)ythv}^N - \bar{\mu}_{rythv}^R \leq -\sigma_{yt} \tau_{ytr} C_r^R; \quad \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5h)$$

$$\begin{aligned} \lambda_{RE(\ell)ythv}^N - \lambda_{SE(\ell)ythv}^N + \mu_{\ell ythv}^L + \bar{\mu}_{\ell ythv}^L - \bar{\mu}_{\ell ythv}^L = 0; \quad \forall \ell \in \Omega^L \setminus \Omega^{L+}, \\ \forall t \in \Omega^T, \forall h \in \Omega^H, \end{aligned} \quad (5i)$$

$$\begin{aligned} \lambda_{RE(\ell)ythv}^N - \lambda_{SE(\ell)ythv}^N + \mu_{\ell ythv}^{L+} + \bar{\mu}_{\ell ythv}^{L+} - \bar{\mu}_{\ell ythv}^L = 0; \quad \forall \ell \in \Omega^{L+}, \\ \forall t \in \Omega^T, \forall h \in \Omega^H, \end{aligned} \quad (5j)$$

$$\lambda_{n(s)yth1v}^N + \frac{\tau_{ytr1}}{\eta_s^{S,D}} \phi_{sythv}^S - \bar{\mu}_{syth1v}^{S,D} \leq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (5k)$$

$$\begin{aligned} \lambda_{n(s)ythv}^N + \frac{\tau_{ytr}}{\eta_s^{S,D}} \mu_{sythv}^S - \bar{\mu}_{sythv}^{S,D} \leq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \\ \forall h \in \Omega^H \setminus \{1\}, \end{aligned} \quad (5l)$$

$$-\lambda_{n(s)ytr1v}^N - \eta_s^{S,C} \tau_{ytr1} \phi_{sythv}^S - \bar{\mu}_{sytr1v}^{S,C} \leq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (5m)$$

$$\begin{aligned} -\lambda_{n(s)ythv}^N - \eta_s^{S,C} \tau_{ytr} \mu_{sythv}^S - \bar{\mu}_{sythv}^{S,C} \leq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \\ \forall h \in \Omega^H \setminus \{1\}, \end{aligned} \quad (5n)$$

$$\begin{aligned} - \sum_{\ell \in \Omega^L \setminus \Omega^{L+} | SE(\ell)=n} \frac{1}{X_{\ell}} \mu_{\ell ythv}^L + \sum_{\ell \in \Omega^L \setminus \Omega^{L+} | RE(\ell)=n} \frac{1}{X_{\ell}} \mu_{\ell ythv}^L \\ - \sum_{\ell \in \Omega^{L+} | SE(\ell)=n} \frac{\bar{v}_{\ell y}^{L(j)}}{X_{\ell}} \mu_{\ell ythv}^{L+} + \sum_{\ell \in \Omega^{L+} | RE(\ell)=n} \frac{\bar{v}_{\ell y}^{L(j)}}{X_{\ell}} \mu_{\ell ythv}^{L+} = 0; \\ \forall n \in \Omega^N \setminus n : ref., \forall t \in \Omega^T, \forall h \in \Omega^H, \end{aligned} \quad (5o)$$

$$\begin{aligned} - \sum_{\ell \in \Omega^L \setminus \Omega^{L+} | SE(\ell)=n} \frac{1}{X_{\ell}} \mu_{\ell ythv}^L + \sum_{\ell \in \Omega^L \setminus \Omega^{L+} | RE(\ell)=n} \frac{1}{X_{\ell}} \mu_{\ell ythv}^L \\ - \sum_{\ell \in \Omega^{L+} | SE(\ell)=n} \frac{\bar{v}_{\ell y}^{L(j)}}{X_{\ell}} \mu_{\ell ythv}^{L+} + \sum_{\ell \in \Omega^{L+} | RE(\ell)=n} \frac{\bar{v}_{\ell y}^{L(j)}}{X_{\ell}} \mu_{\ell ythv}^{L+} + \phi_{nythv}^N = 0; \\ n : ref., \forall t \in \Omega^T, \forall h \in \Omega^H, \end{aligned} \quad (5p)$$

$$\phi_{sythv}^S - \mu_{syth2v}^S + \mu_{syth1v}^S - \bar{\mu}_{syth1v}^S = 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (5q)$$

$$\begin{aligned} \mu_{sythv}^S - \mu_{syth+1v}^S + \mu_{sythv}^S - \bar{\mu}_{sythv}^S = 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \\ \forall h \in \Omega^H \setminus \{1, H\}, \end{aligned} \quad (5r)$$

$$\mu_{sythHv}^S + \phi_{sythv}^S + \mu_{sythv}^S - \bar{\mu}_{sythHv}^S = 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (5s)$$

$$\mu_{\ell ythv}^L, \bar{\mu}_{\ell ythv}^L \geq 0; \quad \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5t)$$

$$\phi_{sythv}^S \geq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \quad (5u)$$

$$\mu_{sythv}^S, \bar{\mu}_{sythv}^S, \bar{\mu}_{sythv}^{S,C}, \bar{\mu}_{sythv}^{S,D} \geq 0; \quad \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5v)$$

$$\bar{\mu}_{dythv}^D \geq 0; \quad \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5w)$$

$$\mu_{gythv}^G, \bar{\mu}_{gythv}^G \geq 0; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (5x)$$

$$\mu_{gythv}^{G,D}, \bar{\mu}_{gythv}^{G,U} \geq 0; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \quad (5y)$$

$$\bar{\mu}_{rythv}^R \geq 0; \quad \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \quad (5z)$$

where set  $\Phi^{ILMP} = \{\xi_y, \bar{p}_{dy}^D, z_{dy}^D, \forall d \in \Omega^D; c_{gy}^G, \bar{p}_{gy}^G, z_{gy}^{G,C}, z_{gy}^{G,P}, \forall g \in \Omega^G; \bar{p}_{ry}^R, z_{ry}^R, \forall r \in \Omega^R; \lambda_{nythv}^N, \forall n \in \Omega^N, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \mu_{\ell ythv}^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \mu_{\ell ythv}^{L+}, \forall \ell \in \Omega^{L+}, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \mu_{\ell ythv}^{L-}, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \phi_{sythv}^S, \phi_{sythv}^{S-}, \forall s \in \Omega^S, \forall t \in \Omega^T, v = k - r^l + 1, \dots, k; \mu_{sythv}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, v = k - r^l + 1, \dots, k; \bar{\mu}_{sythv}^S, \bar{\mu}_{sythv}^{S,C}, \bar{\mu}_{sythv}^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \bar{\mu}_{dythv}^D, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \bar{\mu}_{gythv}^G, \bar{\mu}_{gythv}^{G,D}, \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \bar{\mu}_{gythv}^{G,U}, \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, v = k - r^l + 1, \dots, k; \bar{\mu}_{rythv}^R, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k; \varphi_{nythv}^N, n : ref, \forall t \in \Omega^T, \forall h \in \Omega^H, v = k - r^l + 1, \dots, k\}$  includes the optimization variables of problem (5). Note that the use of the conventional NCCGA implies that constraints (5c)–(5z) are evaluated for  $v = 1, \dots, k$  rather than for  $v = k - r^l + 1, \dots, k$ .

The acceleration technique associated with the relaxation of the inner-loop master problem is used, i.e., it is solved by considering only the constraints and variables associated with the latest realization of the binary operating decision variables determined by the inner-loop subproblem to speed up its solution procedure. More cutting planes associated with realizations of the third-level binary variables previously identified by solving the inner-loop subproblem are considered in the formulation of the inner-loop master problem (5) when the relaxed inner-loop iteration counter  $r^l$  increases, i.e., it works in a similar manner to the relaxation of the outer-loop master problem explained in Section 3.1. In this case, the solution procedure is repeated until the optimal objective function value of the inner-loop master problem decreases with respect to its value in the previous inner-loop iteration or until  $r^l > k$ .

The objective function (5a) is equivalent to (2a), but the operating costs for year  $y$  are approximately represented using the term  $\xi_y$ . Constraints (5c) impose an upper bound for  $\xi_y$  defined by the lower-level dual objective function, while constraints (5d)–(5z) are associated with the lower-level dual feasibility constraints. Note that constraints (5c)–(5z) are evaluated for given values of the binary variables  $u_{gythv}^{G(v)}$  and  $u_{sythv}^{S(v)}$  identified at inner-loop iteration  $v$ .

Problem (5) is a MINLP problem featuring non-linear terms  $\bar{p}_{dy}^D \lambda_{n(dy)thv}^N$ ,  $\bar{p}_{dy}^D \bar{\mu}_{dythv}^D$ ,  $\bar{p}_{gy}^G \bar{\mu}_{gythv}^G$ , and  $\bar{p}_{ry}^R \bar{\mu}_{rythv}^R$  included in constraints (5c), which can be rewritten as the sum of linear terms and the product of binary variables and continuous dual variables. For instance, variables  $\bar{p}_{dy}^D$  are replaced with terms  $\bar{p}_d^D (1 + \bar{\xi}_d^D)^{y-1} + \hat{p}_d^D (1 + \bar{\xi}_d^D)^{y-1} z_{dy}^D$ , which represent the sum of the forecast values and the maximum deviations of the peak power consumption of loads. Note that these terms evolve at each year of the planning horizon according to the annual evolution rates  $\bar{\xi}_d^D$  and  $\hat{\xi}_d^D$ . As a result of this transformation, non-linear terms  $\bar{p}_{dy}^D \lambda_{n(dy)thv}^N$  are replaced with the sum of terms  $\bar{p}_d^D (1 + \bar{\xi}_d^D)^{y-1} \lambda_{n(dy)thv}^N$  and  $\hat{p}_d^D (1 + \bar{\xi}_d^D)^{y-1} z_{dy}^D \lambda_{n(dy)thv}^N$ . Problem (5) can be, therefore, recast as an MILP problem by using the exact linearization described in [30].

Note that the upper bound of the inner loop  $UB^l$  is updated to the optimal objective function value of the inner-loop master problem (5). Moreover, once the convergence of the inner loop has been attained

for all years, the upper bound of the outer loop  $UB^0$  is updated to the total worst-case cost, i.e.,  $\sum_{y \in \Omega^Y} \frac{1}{(1 + \kappa)^{y-1}} \left( \frac{\xi_y^*}{1 + \kappa} + \sum_{\ell \in \Omega^{L+}} I_{\ell}^L v_{\ell y}^{L(j)} \right)$ .

### 3.2.2. Inner-loop subproblem

The inner-loop subproblem is equivalent to the lower-level problem (3) for given expansion-decision variables  $v_{\ell y}^{L(j)}$ , where the uncertain variables are set to the values identified by the inner-loop master problem at the previous inner-loop iteration. The inner-loop subproblem for year  $y$  at outer-loop iteration  $j$  and inner-loop iteration  $k$  is formulated as the following MILP problem:

$$\min_{\Phi^{ILSP}} \sum_{t \in \Omega^T} \sigma_{yt} \sum_{h \in \Omega^H} \tau_{yth} \left( \sum_{g \in \Omega^G} c_{gy}^{G(k)} p_{gyth}^G + \sum_{r \in \Omega^R} C_r^R (r_{ryth}^R \bar{p}_{ry}^{R(k)} - p_{ryth}^R) + \sum_{d \in \Omega^D} C_d^{LS} p_{dyth}^{LS} \right) \quad (6a)$$

subject to:

$$\sum_{g \in \Omega_n^G} p_{gyth}^G + \sum_{r \in \Omega_n^R} p_{ryth}^R + \sum_{\ell \in \Omega^{L+} | RE(\ell) = n} p_{\ell yth}^L - \sum_{\ell \in \Omega^L | SE(\ell) = n} p_{\ell yth}^L + \sum_{s \in \Omega_n^S} (p_{syth}^{S,D} - p_{syth}^{S,C}) = \sum_{d \in \Omega_n^D} (r_{dyth}^D \bar{p}_{dy}^{D(k)} - p_{dyth}^{LS}); \quad \forall n \in \Omega^N, \quad (6b)$$

$$p_{\ell yth}^L = \frac{v_{\ell y}^{L(j)}}{X_{\ell}} (\theta_{SE(\ell)yth} - \theta_{RE(\ell)yth}); \quad \forall \ell \in \Omega^{L+}, \forall t \in \Omega^T, \quad (6c)$$

$$0 \leq p_{dyth}^{LS} \leq r_{dyth}^D \bar{p}_{dy}^{D(k)}; \quad \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (6d)$$

$$u_{gyth}^G p_{gyth}^G \leq p_{gyth}^G \leq u_{gyth}^G \bar{p}_{gy}^{G(k)}; \quad \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (6e)$$

$$0 \leq p_{ryth}^R \leq r_{ryth}^R \bar{p}_{ry}^{R(k)}; \quad \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, \quad (6f)$$

$$\text{Constraints (3c), (3e)–(3l), (3n), (3p), and (3r),} \quad (6g)$$

where set  $\Phi^{ILSP} = \{p_{gyth}^G, u_{gyth}^G, \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H; p_{dyth}^{LS}, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H; \bar{p}_{ryth}^R, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H; p_{\ell yth}^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall h \in \Omega^H; e_{syth}^{S-}, p_{syth}^{S,C}, p_{syth}^{S,D}, u_{syth}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H; \theta_{nyth}, \forall n \in \Omega^N, \forall t \in \Omega^T, \forall h \in \Omega^H\}$  includes the optimization variables of problem (6).

The objective function (6a) and constraints (6b)–(6g) are analogous to the objective function (3a) and constraints (3b)–(3r), where expansion-decision variables  $v_{\ell y}^{L(j)}$  are set to the investment plan resulting from the outer-loop master problem (4) at outer-loop iteration  $j$ , and the values of the uncertain variables  $c_{gy}^{G(k)}$ ,  $\bar{p}_{dy}^{D(k)}$ ,  $\bar{p}_{gy}^{G(k)}$ , and  $\bar{p}_{ry}^{R(k)}$  are identified by solving inner-loop master problem (5) at the previous inner-loop iteration.

Note that the lower bound of the inner loop  $LB^l$  is updated to the optimal objective function value of the inner-loop subproblem (6).

### 3.3. ADA-based initialization of the inner loop

The computational time of the NCCGA is associated with the number of iterations needed to attain the convergence of the inner loop, since the number of variables and constraints of the inner-loop master problem is increased at each inner-loop iteration. Note that the inner loop is initialized by considering given values of the uncertain variables when the inner-loop subproblem is solved at the first inner-loop iteration. The variables that model the uncertainty realizations can, therefore, be initialized at the beginning of the inner loop to the solution of the outer-loop subproblem obtained by using heuristic methods in order to reduce the number of inner-loop iterations and the computational time. In particular, we apply the ADA [29] to solve the inner-loop master problem (5), while the inner-loop subproblem (6) is solved by using an exact solution procedure. Note that the solution of the uncertain variables obtained at this point may not be optimal since the ADA is a heuristic technique. Thus, the outer-loop

subproblem is solved again, but this second time the uncertain variables are initialized to the uncertainty realization previously determined, and the non-linearities of the inner-loop master problem are tackled by using the exact linearization described in [30], which guarantees the convergence of the NCCGA to the global optimal solution.

Bilinear problems can be solved by applying the ADA, as done for instance in [31] to tackle the inner-loop master problem, which implies iteratively solving two linear programming (LP) problems. Next, the formulations of these two LP problems are presented. The reader is referred to [29] for additional information about the ADA.

### 3.3.1. First LP problem

The first LP problem for given expansion-decision variables  $\bar{v}_{\ell y}^{L(j)}$ , binary operating decision variables  $u_{gyth}^{G(v)}$  and  $u_{syth}^{S(v)}$ , and uncertain variables  $\bar{p}_{dy}^{D(o)}$ ,  $\bar{p}_{gy}^{G(o)}$ , and  $\bar{p}_{ry}^{R(o)}$  for year  $y$  at outer-loop iteration  $j$ , inner-loop iteration  $k$ , and ADA-loop iteration  $o$  is formulated as follows:

$$\max_{\Phi^{ILMP,P}} \xi_y^P \quad (7a)$$

subject to:

$$\bar{c}_{gy}^G = \bar{c}_g^G (1 + \bar{\zeta}_g^G)^{y-1} + \hat{c}_g^G (1 + \hat{\zeta}_g^G)^{y-1} a_{gy}^G, \quad \forall g \in \Omega^G, \quad (7b)$$

$$0 \leq a_{gy}^{G,C} \leq 1; \quad \forall g \in \Omega^G, \quad (7c)$$

$$\sum_{g \in \Omega^G} a_{gy}^{G,C} \leq \Gamma^{G,C}, \quad (7d)$$

$$\begin{aligned} \xi_y^P \leq & \sum_{i \in \Omega^I} \left( \sum_{h \in \Omega^H} \left( \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^{D(o)} \lambda_{n(d)ythv}^N - \sum_{\ell \in \Omega^L} \bar{P}_{\ell}^L (\mu_{\ell ythv}^L + \bar{\mu}_{\ell ythv}^L) \right) \right. \\ & - \sum_{s \in \Omega^S} \left( u_{syth}^{S(v)} \bar{P}_s^{S,C} \bar{\mu}_{sythv}^{S,C} + (1 - u_{syth}^{S(v)}) \bar{P}_s^{S,D} \bar{\mu}_{sythv}^{S,D} - \bar{E}_s^S \mu_{sythv}^S \right. \\ & \left. \left. + \bar{E}_s^S \bar{\mu}_{sythv}^S \right) \right) + \sum_{g \in \Omega^G} u_{gyth}^{G(v)} \left( \bar{P}_g^G \mu_{gythv}^{G(o)} - \bar{P}_{gy}^{G(o)} \bar{\mu}_{gythv}^{G(o)} \right) \\ & - \sum_{r \in \Omega^R} \gamma_{ryth}^R \bar{p}_{ry}^{R(o)} \left( \bar{\mu}_{rythv}^{R(o)} - \sigma_{yt} \tau_{ytr} C_r^R \right) - \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^{D(o)} \bar{\mu}_{dythv}^{D(o)} \\ & + \sum_{s \in \Omega^S} E_{sythv}^S \left( \phi_{sythv}^S + \bar{\phi}_{sythv}^S \right) \\ & - \sum_{h \in \Omega^H \setminus \{1\}} \sum_{g \in \Omega^G} \left( R_g^{G,D} \mu_{gythv}^{G,D} + R_g^{G,U} \bar{\mu}_{gythv}^{G,U} \right); \quad \nu = 1, \dots, k, \quad (7e) \end{aligned}$$

$$\text{Constraints (5d)–(5z),} \quad (7f)$$

where set  $\Phi^{ILMP,P} = \{\xi_y^P, a_{gy}^{G,C}, c_{gy}^G, \forall g \in \Omega^G; \lambda_{nythv}^N, \forall n \in \Omega^N, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \mu_{\ell ythv}^L, \forall \ell \in \Omega^L \setminus \Omega^{L+}, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \mu_{\ell ythv}^{L+}, \forall \ell \in \Omega^{L+}, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \phi_{sythv}^S, \bar{\phi}_{sythv}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \nu = 1, \dots, k; \mu_{sythv}^S, \bar{\mu}_{sythv}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \nu = 1, \dots, k; \mu_{sythv}^{S,C}, \bar{\mu}_{sythv}^{S,C}, \mu_{sythv}^{S,D}, \bar{\mu}_{sythv}^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \bar{p}_{dythv}^D, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \mu_{gythv}^G, \bar{\mu}_{gythv}^G, \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \mu_{gythv}^{G,D}, \bar{\mu}_{gythv}^{G,D}, \forall g \in \Omega^G, \forall t \in \Omega^T, \forall h \in \Omega^H \setminus \{1\}, \nu = 1, \dots, k; \bar{\mu}_{rythv}^R, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k; \phi_{nythv}^N, n : ref, \forall t \in \Omega^T, \forall h \in \Omega^H, \nu = 1, \dots, k\}$  includes the optimization variables of problem (7). Note that it is not necessary to consider the constraints of the inner-loop master problem (5) that involves only variables from set  $\Phi^{ILMP,Q}$ , which is described in Section 3.3.3, in the formulation of problem (7).

### 3.3.2. Second LP problem

The second LP problem for given expansion-decision variables  $\bar{v}_{\ell y}^{L(j)}$ , binary operating decision variables  $u_{gyth}^{G(v)}$  and  $u_{syth}^{S(v)}$ , and dual variables of the lower-level problem, such as  $\lambda_{nythv}^{N(o)}$ , for year  $y$  at outer-loop iteration

$j$ , inner-loop iteration  $k$ , and ADA-loop iteration  $o$  is formulated as follows:

$$\max_{\Phi^{ILMP,Q}} \xi_y^Q \quad (8a)$$

subject to:

$$\bar{p}_{dy}^D = \bar{p}_d^D (1 + \bar{\zeta}_d^D)^{y-1} + \hat{p}_d^D (1 + \hat{\zeta}_d^D)^{y-1} a_{dy}^D, \quad \forall d \in \Omega^D, \quad (8b)$$

$$\bar{p}_{gy}^G = \bar{p}_g^G (1 - \bar{\zeta}_g^{G,P})^{y-1} - \hat{p}_g^G (1 + \hat{\zeta}_g^{G,P})^{y-1} a_{gy}^{G,P}, \quad \forall g \in \Omega^G, \quad (8c)$$

$$\bar{p}_{ry}^R = \bar{p}_r^R (1 + \bar{\zeta}_r^R)^{y-1} - \hat{p}_r^R (1 + \hat{\zeta}_r^R)^{y-1} a_{ry}^R, \quad \forall r \in \Omega^R, \quad (8d)$$

$$0 \leq a_{dy}^D \leq 1; \quad \forall d \in \Omega^D, \quad (8e)$$

$$0 \leq a_{gy}^{G,P} \leq 1; \quad \forall g \in \Omega^G, \quad (8f)$$

$$0 \leq a_{ry}^R \leq 1; \quad \forall r \in \Omega^R, \quad (8g)$$

$$\sum_{d \in \Omega^D} a_{dy}^D \leq \Gamma^D, \quad (8h)$$

$$\sum_{g \in \Omega^G} a_{gy}^{G,P} \leq \Gamma^{G,P}, \quad (8i)$$

$$\sum_{r \in \Omega^{R,S}} a_{ry}^R \leq \Gamma^{R,S}, \quad (8j)$$

$$\sum_{r \in \Omega^{R,W}} a_{ry}^R \leq \Gamma^{R,W}, \quad (8k)$$

$$\begin{aligned} \xi_y^Q \leq & \sum_{i \in \Omega^I} \left( \sum_{h \in \Omega^H} \left( \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^{D(o)} \lambda_{n(d)ythv}^{N(o)} - \sum_{\ell \in \Omega^L} \bar{P}_{\ell}^L (\mu_{\ell ythv}^{L(o)} + \bar{\mu}_{\ell ythv}^{L(o)}) \right) \right. \\ & - \sum_{s \in \Omega^S} \left( u_{syth}^{S(v)} \bar{P}_s^{S,C} \bar{\mu}_{sythv}^{S,C(o)} + (1 - u_{syth}^{S(v)}) \bar{P}_s^{S,D} \bar{\mu}_{sythv}^{S,D(o)} - \bar{E}_s^S \mu_{sythv}^{S(o)} \right. \\ & \left. \left. + \bar{E}_s^S \bar{\mu}_{sythv}^{S(o)} \right) \right) + \sum_{g \in \Omega^G} u_{gyth}^{G(v)} \left( \bar{P}_g^G \mu_{gythv}^{G(o)} - \bar{P}_{gy}^{G(o)} \bar{\mu}_{gythv}^{G(o)} \right) \\ & - \sum_{r \in \Omega^R} \gamma_{ryth}^R \bar{p}_{ry}^{R(o)} \left( \bar{\mu}_{rythv}^{R(o)} - \sigma_{yt} \tau_{ytr} C_r^R \right) - \sum_{d \in \Omega^D} \gamma_{dyth}^D \bar{p}_{dy}^{D(o)} \bar{\mu}_{dythv}^{D(o)} \\ & + \sum_{s \in \Omega^S} E_{sythv}^S \left( \phi_{sythv}^{S(o)} + \bar{\phi}_{sythv}^{S(o)} \right) \\ & - \sum_{h \in \Omega^H \setminus \{1\}} \sum_{g \in \Omega^G} \left( R_g^{G,D} \mu_{gythv}^{G,D(o)} + R_g^{G,U} \bar{\mu}_{gythv}^{G,U(o)} \right), \quad \nu = 1, \dots, k, \quad (8l) \end{aligned}$$

where set  $\Phi^{ILMP,Q} = \{\xi_y^Q, a_{dy}^D, \bar{p}_{dy}^D, \forall d \in \Omega^D; a_{gy}^{G,P}, \bar{p}_{gy}^G, \forall g \in \Omega^G; a_{ry}^R, \bar{p}_{ry}^R, \forall r \in \Omega^R\}$  includes the optimization variables of problem (8). Note that it is not necessary to consider the constraints of the inner-loop master (5) problem that involves only variables from set  $\Phi^{ILMP,P}$ , which is described in Section 3.3.3, in the formulation of problem (8).

### 3.3.3. Steps of the ADA

The ADA involves the following steps:

- (1) First, variables of the inner-loop master problem are distributed in two sets, namely,  $\Phi^{ILMP,P}$  and  $\Phi^{ILMP,Q}$ . We specifically distribute them with the aim of minimizing the number constraints considered in the problems solved in Steps (2) and (3). As a result, set  $\Phi^{ILMP,P}$  is composed of the lower-level dual variables for given values of the binary operating decision variables, and the uncertain variables related to the marginal production cost of conventional generating units  $c_{gy}^G$ , while set  $\Phi^{ILMP,Q}$  is composed of the remaining uncertain variables, i.e.,  $\bar{p}_{dy}^D$ ,  $\bar{p}_{gy}^G$ , and  $\bar{p}_{ry}^R$ . Moreover, we set the iteration counter of the ADA  $o$  to 1 and initialize the values of variables included in  $\Phi^{ILMP,Q(1)}$  to their forecast values.
- (2) Problem (7) is solved. Note that variables from set  $\Phi^{ILMP,Q}$  are considered to be equal to the values from the solution obtained in Step (3) of the previous ADA-loop iteration if iteration counter  $o$  is greater than 1. Otherwise, the values are those set in Step (1).

- (3) Problem (8) is solved. Note that variables from set  $\Phi^{\text{ILMP,P}}$  are considered to be equal to the values from the solution obtained in Step (2).
- (4) The algorithm stops if the relative difference between the optimal objective function value of the problems solved in Steps (2) and (3) is lower than a predefined tolerance. Otherwise, increase the ADA-loop iteration counter by one and go to Step (2).

With regard to the convergence of the ADA, the author of [29] shows in Proposition 2.3 that the ADA converges to a KKT point in a finite number of steps when the feasible regions of the two problems involved in the ADA are bounded. Note that a maximum number of iterations of the ADA and the inner loop of the NCCGA can be imposed during the solution procedure of the first outer-loop subproblem at each outer-loop iteration. Hence, if the maximum number of iterations is achieved before obtaining the convergence, the uncertain parameters are initialized to the uncertainty realization associated with the last iteration of the ADA when the second outer-loop subproblem is addressed.

### 3.4. Algorithm

The flowchart of the NCCGA combined with the two exact acceleration techniques is illustrated in Fig. 1. The reader is referred to [32,34] for further information on the detailed algorithms of the NCCGA and the two exact acceleration techniques, respectively.

## 4. Numerical results

This section presents the numerical results obtained from two case studies in which the proposed multi-year two-stage ARO TNEP approach was considered. We handled this problem by following the solution procedure described in Section 3, in which the NCCGA is combined with two exact acceleration techniques. A Gigabyte MD71-HB0 with 768 GB of RAM and 2 Intel Xeon Cascade Lake Gold 6248RR at 3.0 GHz was used to run the simulations by applying CPLEX 20.1.0.1 [37] under GAMS 38.3.0 [38].

The operational variability of the electrical demand and the production of solar- and wind-power units was modeled by using a set of RDs obtained from the combination of the modified maximum dissimilarity algorithm [39] and the priority chronological-time period clustering [40]. The former aggregation technique was specifically applied to group historical days into 10 RDs, and the latter clustering method was then used to reduce the number of RTPs of each RD from 24 to 8, since hourly historical data were considered as input data. Note that we used these two aggregation techniques owing to the perks of their combination shown in [41], but the formulation of the multi-year two-stage ARO TNEP problem makes it possible to consider any other clustering techniques. The reader is referred to [42] for further information on the data of the case studies analyzed.

### 4.1. IEEE 24-bus reliability test system

We analyzed the performance of the multi-year two-stage ARO TNEP approach by using a modified version of the IEEE 24-bus Reliability Test System (RTS) [43]. The network comprises 24 buses, 10 conventional generating units, 5 solar-power units, 5 wind-power units, 5 storage facilities, 17 loads, and 38 existing transmission lines. Moreover, we considered the possibility of building 24 candidate transmission lines, and these investment decisions can be made in each year through a planning horizon of 10 years. We imposed a relative stopping tolerance of  $10^{-2}$  for the different loops involved in the solution procedure, and the relative optimality gap for the branch-and-cut algorithm of CPLEX was set to  $10^{-3}$ . Five different uncertainty levels were considered to test this case study: null, low, medium, high, and maximum. The values of the uncertainty budgets associated with these five uncertainty levels are shown in Table 2.

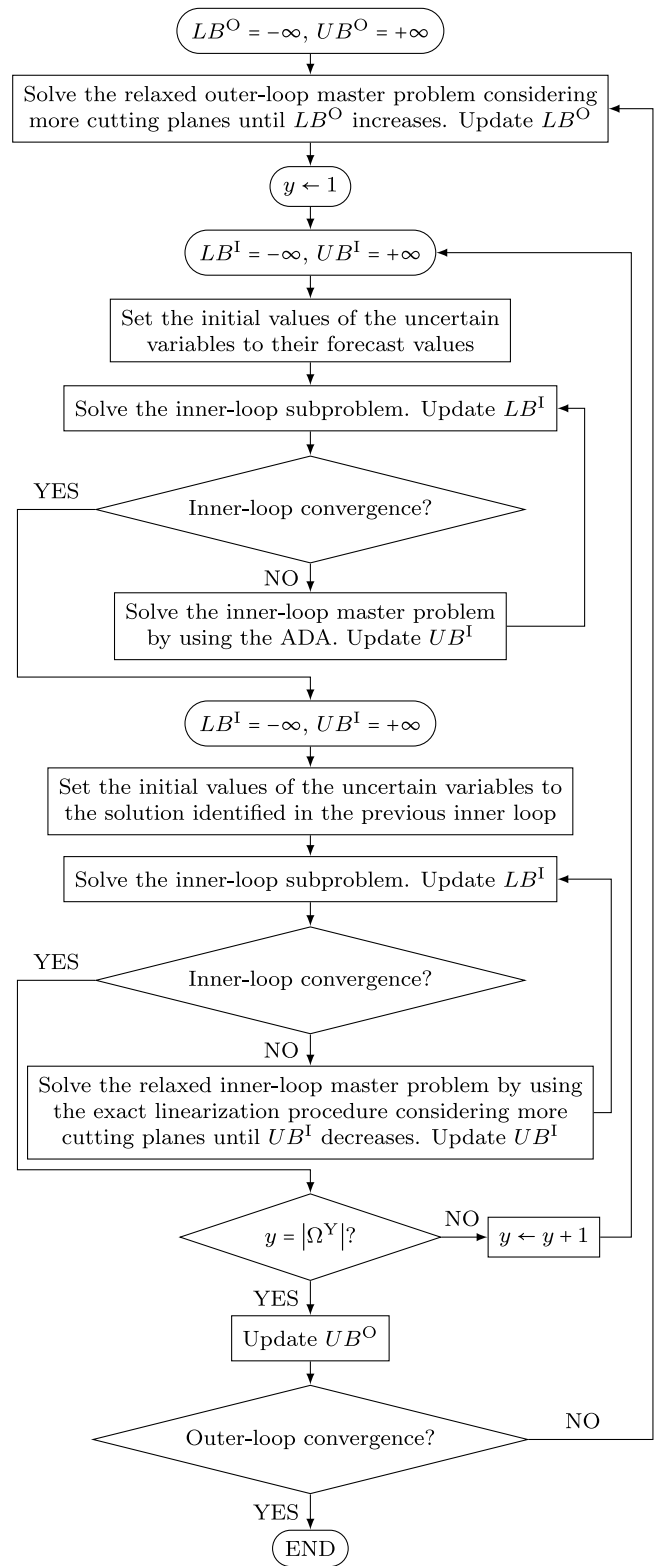


Fig. 1. Flowchart of the NCCGA combined with the ADA-based initialization of the inner loop and the relaxation of the outer- and inner-loop master problems.

We solved the multi-year two-stage ARO TNEP problem by considering the proposed approach, but also the sequential static and static procedures. Note that the formulation of the problem to consider these approaches implies some changes as explained in Appendix.

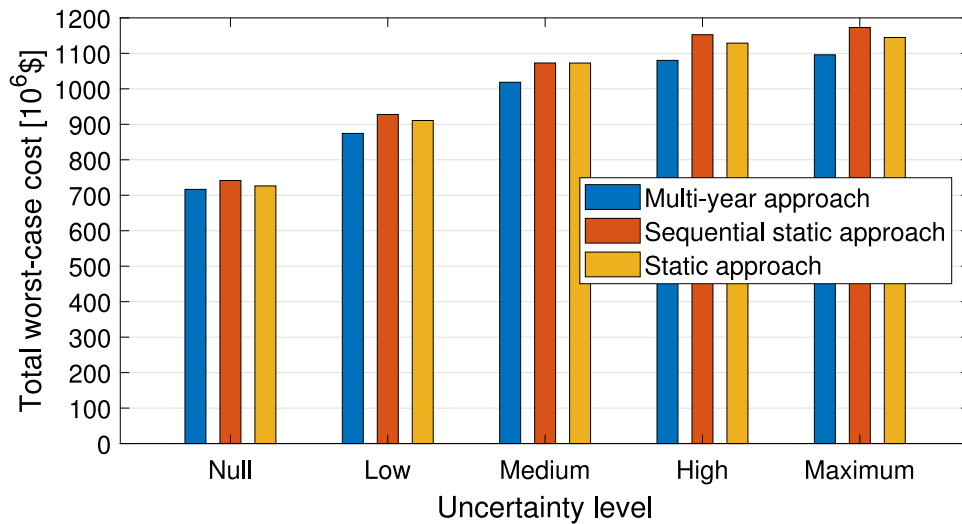


Fig. 2. IEEE 24-bus RTS: total worst-case cost obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels.

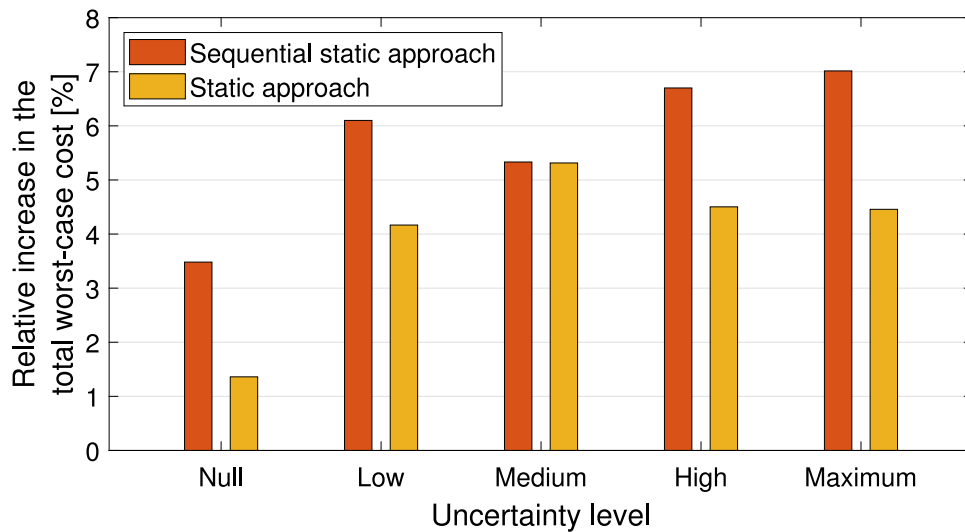


Fig. 3. IEEE 24-bus RTS: relative increase in the total worst-case cost obtained by using the sequential static, and static approaches at different uncertainty levels.

Table 2

IEEE 24-bus RTS: uncertainty budgets at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
$I^D$	0	3	8	14	17
$I^{G,C}$	0	2	5	8	10
$I^{G,P}$	0	2	5	8	10
$I^{R,S}$	0	1	3	4	5
$I^{R,W}$	0	1	3	4	5

Fig. 2 shows the total worst-case cost obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels. Note that the total worst-case annualized cost was minimized when solving the static two-stage ARO TNEP problem since only a target year was considered. The total worst-case cost associated with the static approach was, then, computed by solving the multi-year two-stage ARO TNEP problem for given investment decisions obtained from the solution of the static problem. This procedure was not required to compute the total worst-case cost associated with the sequential static approach since the total worst-case cost of each year of the planning horizon had already been computed during its solution procedure. Observe that increases in the uncertainty level translate into greater total worst-case costs for the three approaches considered. Moreover,

the use of the multi-year model leads to lower total worst-case costs in comparison with the other two approaches at all the uncertainty levels analyzed. The use of the sequential static and static approaches involves relative increases in the total worst-case cost between 1% and 7% in comparison with the multi-year approach, as shown in Fig. 3.

The three approaches analyzed involve different values of the total worst-case cost since the investment plans identified are not the same, as shown in Fig. 4. Note that more than one color is used in a cell when the same investment decision is identified by different approaches. Fig. 5 shows that these mismatches in the expansion decisions result in different investment costs. Observe that the greatest investment costs are obtained at all the uncertainty levels analyzed when the static approach is used because all investment decisions are made at the beginning of the planning horizon and more transmission lines are built in comparison with the solution of the other models. Additionally, similar investment plans are obtained by using the multi-year and sequential static approaches, but transmission lines are built earlier in most of the cases when the former approach is considered. The reason for this advance in the investment decisions is that the use of the multi-year approach allows the comprehensive view of the entire planning horizon to be considered when the expansion decisions are made. In other words, the multi-year approach may identify that a certain



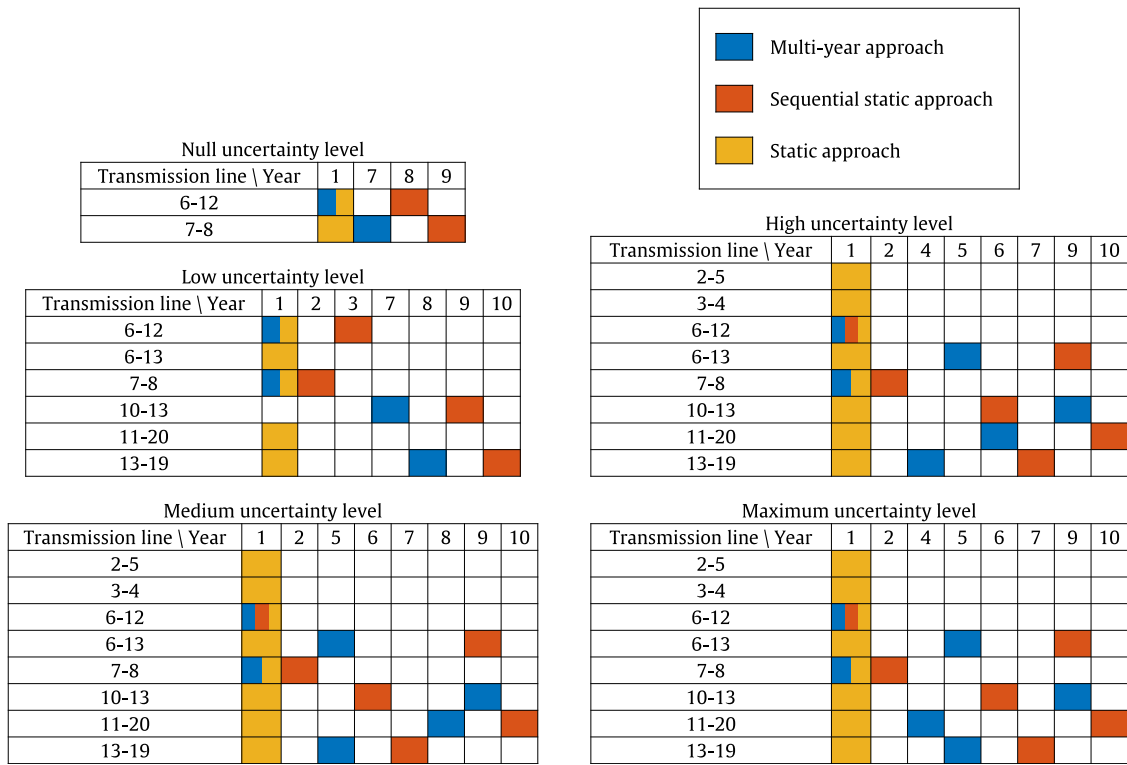


Fig. 4. IEEE 24-bus RTS: investment plan obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels.

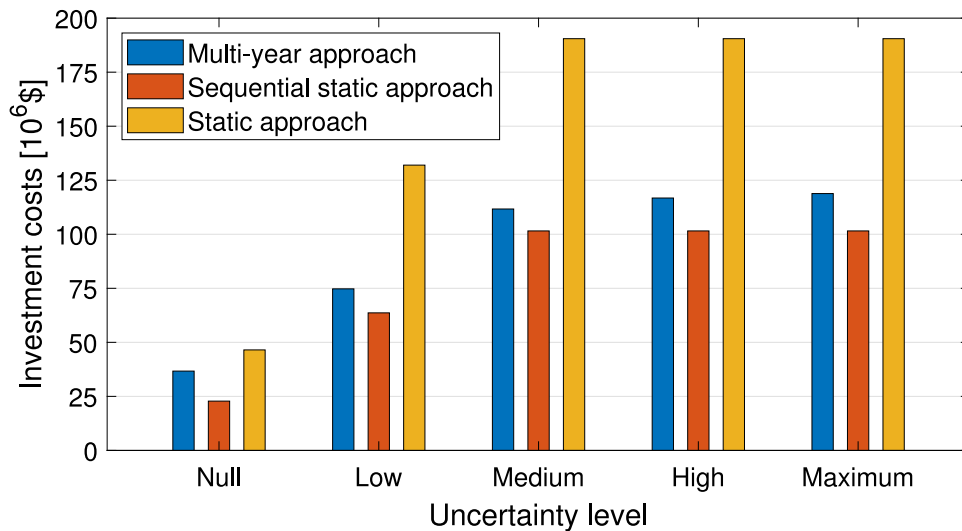


Fig. 5. IEEE 24-bus RTS: investment costs obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels.

transmission line should be built in a year taking into consideration the conditions of the power system in the following years, while the sequential static approach will made expansion decisions on the basis of only the conditions of the power system in the year under study. It is worth mentioning that some new transmission lines are built earlier as the uncertainty level is increased when using the multi-year approach. For instance, Fig. 4 shows that this occurs to the transmission line that joins nodes 11 and 20 at the medium, high, and maximum uncertainty levels.

With regard to the solution procedure, Fig. 6 shows the computational time of the proposed multi-year two-stage ARO TNEP problem obtained by using the modified NCCGA described in Section 3 and the conventional NCCGA at different uncertainty levels. Observe that the computational times significantly increase when the conventional

NCCGA is applied without any acceleration technique. On the one hand, the computational time varies between 6 h and 14 h at the non-null uncertainty levels analyzed when the modified NCCGA is applied. On the other, the use of the conventional NCCGA leads to computational times of between 43 h and 46 h at the medium, high, and maximum uncertainty levels, while the solution at the low uncertainty level has not been attained after 100 h.

Furthermore, Table 3 shows the number of outer-loop iterations and maximum number of inner-loop iterations needed to attain the convergence of both loops obtained by using the modified NCCGA and the conventional NCCGA to solve the multi-year two-stage ARO TNEP problem at different uncertainty levels. These results confirm that the ADA-based initialization of the inner-loop described in Section 3.3.3 reduces the number of inner-loop iterations. It is worth mentioning that

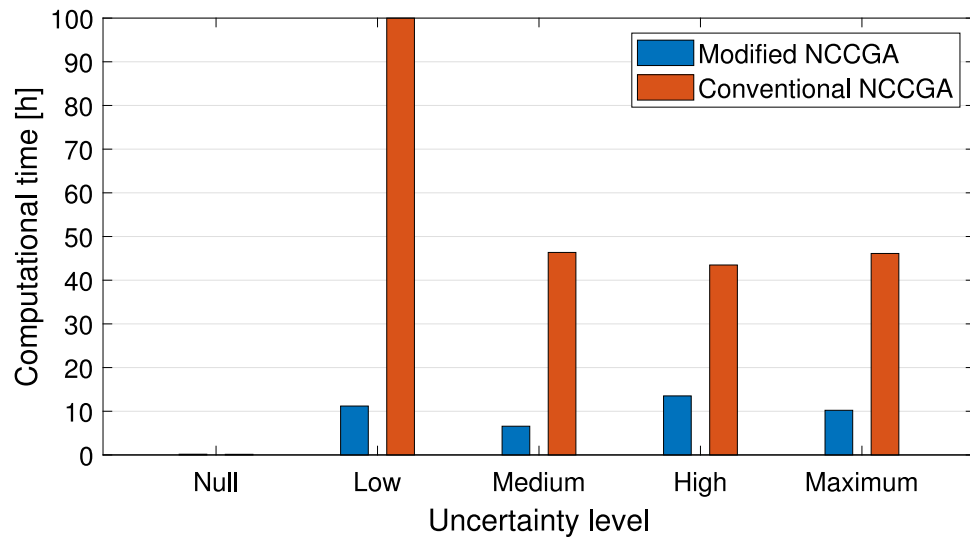


Fig. 6. IEEE 24-bus RTS: computational time of the multi-year two-stage ARO TNEP problem obtained by using the modified and conventional NCCGA at different uncertainty levels.

Table 3

IEEE 24-bus RTS: number of outer-loop iterations and maximum number of inner-loop iterations needed to attain the convergence of both loops obtained by using the modified and conventional NCCGA to solve the multi-year two-stage ARO TNEP problem at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
Number of outer-loop iterations of the modified NCCGA	1	4	2	2	2
Number of outer-loop iterations of the conventional NCCGA	1	3*	2	2	2
Maximum number of inner-loop iterations of the modified NCCGA	2	3	2	2	2
Maximum number of inner-loop iterations of the conventional NCCGA	2	3*	3	3	3

\*Problem not solved in less than 100 h.

the maximum value of relaxed outer- and inner-loop iteration counters  $r^O$  and  $r^I$  is 1 for all cases in which the modified NCCGA has been used, which highlights the perks of relaxing the master problems.

#### 4.2. IEEE 118-bus test system

We also analyzed the performance of the multi-year two-stage ARO TNEP approach by using a modified version of the IEEE 118-bus Test System (TS) [44]. This network comprises 118 buses, 40 conventional generating units, 16 solar-power units, 12 wind-power units, 7 storage facilities, 91 loads, 186 existing transmission lines, and 18 candidate transmission lines. Moreover, we considered a planning horizon of 20 years. The relative stopping tolerance of the different loops involved in the solution procedure and the relative optimality gap for the branch-and-cut algorithm of CPLEX were set to  $5 \cdot 10^{-3}$ .

The uncertainty was modeled in this case study by considering groups for the uncertain parameters that may undergo deviations from their forecast values. This simplification was considered in order to reduce the computational burden of the problem since in this case study a larger test system was analyzed. We assumed that the 91 loads were equally distributed among 13 groups based on their forecast peak power consumption. The first group is composed of the 7 loads associated with the greatest forecast peak power consumption, while the last group contains the 7 loads linked to the lowest forecast peak power consumption. Thus, if the load of a specific group undergoes an increase in its forecast peak power consumption, a deviation is also undergone by the remaining loads of that group. The values given

Table 4

IEEE 118-bus TS: uncertainty budgets at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
$\Gamma^D$	0	3	6	9	13
$\Gamma^{G,C}$	0	1	2	3	4
$\Gamma^{G,P}$	0	2	4	6	8
$\Gamma^{R,S}$	0	1	2	4	5
$\Gamma^{R,W}$	0	1	2	3	4

to the uncertainty budget  $\Gamma^D$  were, therefore, between 0 and 13. Similarly, the 40 conventional generating units, the 16 solar-power units, and the 12 wind-power units were equally distributed among 8, 5, and 4 groups, respectively, based on their forecast capacity. With regard to the marginal production cost of conventional generating units, these units were distributed among 4 groups since we considered only the following forecast values: \$10/MWh, \$20/MWh, \$30/MWh, and \$40/MWh. The case study was analyzed at five uncertainty levels, which differ from each other in the values given to the uncertainty budgets, as shown in Table 4. Note that in this case study loads and generating units with similar characteristics are grouped together and the uncertainty budgets represent the maximum number of groups that can undergo deviations from their forecast values.

##### 4.2.1. Impact of modeling the multi-year nature

We compared the results of the multi-year two-stage ARO TNEP problem obtained by using the multi-year, sequential static, and static approaches. The total worst-case costs obtained by using these approaches at different uncertainty levels are shown in Fig. 7. Observe that the use of the sequential static and static approaches leads to greater total worst-case costs than those obtained when the multi-year approach is considered at the five uncertainty levels analyzed. These differences are highlighted in Fig. 8, which illustrates that the non-multi-year approaches involve relative increases in the total worst-case cost between 0.5% and 3%. Note that Fig. 8 shows that the expansion decisions determined by using the sequential static approach leads to total worst-case costs closer to the optimal solutions associated with the use of the multi-year approach than that attained when the static approach is applied. However, the results are opposed in the previous case study as shown in Fig. 3. Hence, it cannot be concluded that the static approach performs better than the sequential static model or vice versa. The conclusion that can be inferred from these results is that the use of both the static and the sequential static approaches leads to

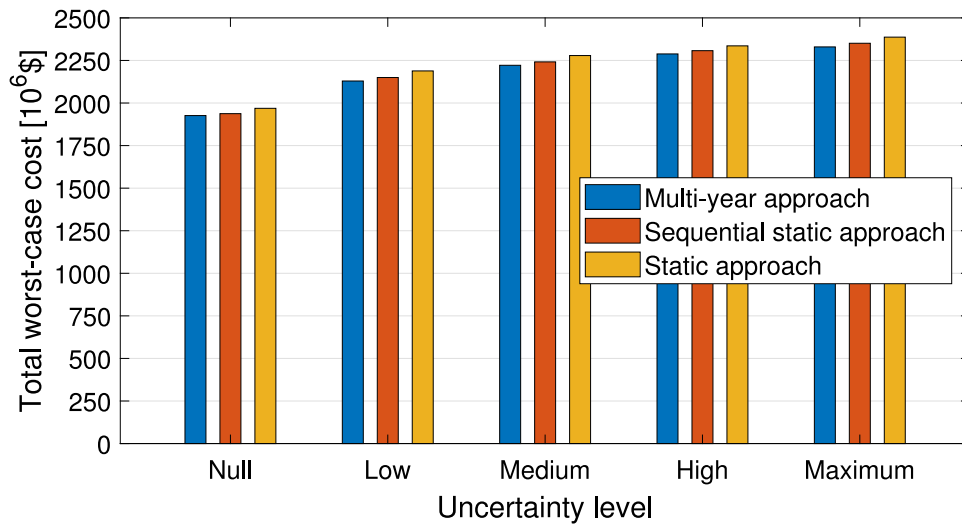


Fig. 7. IEEE 118-bus TS: total worst-case cost obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels.

investment plans that involve greater total worst-case costs than the expansion decisions obtained when the multi-year approach is used.

With regard to the investment plans, the use of the multi-year, sequential static, and static approaches leads to different expansion decisions at the uncertainty levels analyzed, as shown in Fig. 9. Observe that the conclusions inferred from the numerical results of this case study are similar to those derived from the IEEE 24-bus RTS.

Moreover, Fig. 10 shows the computational time of the multi-year two-stage ARO TNEP problem obtained by using the modified NCCGA and the conventional NCCGA at different uncertainty levels. On the one hand, the use of the modified NCCGA involves computational times of between 4 h and 8 h to solve the multi-year two-stage ARO TNEP problem at the non-null uncertainty levels analyzed. On the other, the use of the conventional NCCGA involves a computational time of 67.70 h at the low uncertainty level, while the solutions at the remaining non-null uncertainty levels have not been attained after 100 h. Furthermore, Table 5 shows the number of outer-loop iterations and maximum number of inner-loop iterations needed to attain the convergence of both loops obtained by using the modified NCCGA and the conventional NCCGA to solve the multi-year two-stage ARO TNEP problem at different uncertainty levels. The conclusions inferred from these results are similar to those obtained in the previous case study, i.e., the use of the ADA-based initialization of the inner-loop may lead to reductions in the number of inner-loop iterations and, therefore, computational times lower than those attained when the conventional NCCGA is applied. Moreover, the maximum value of  $r^O$  and  $r^O$  is also 1 in this case study for all cases in which the modified NCCGA has been used.

#### 4.2.2. Impact of modeling the detailed operation of power systems

Many previous two-stage ARO TNEP approaches presented in the technical literature ignore certain features used to model the detailed operation of power systems, as shown in Table 1. The impact of including these features in two-stage ARO TNEP models is highlighted hereunder.

We solved the multi-year two-stage ARO TNEP problem at different uncertainty levels by using a model in which we ignored the ramping limits and commitment statuses of conventional generating units, as well as the charging/discharging statuses of storage facilities. This is called the relaxed model hereon, while the multi-year two-stage ARO TNEP model described in Section 2 is called the benchmark approach. We used the CCGA [24] combined with the second exact acceleration technique described in Section 3.2 to solve the relaxed approach. Note

Table 5

IEEE 118-bus TS: number of outer-loop iterations and maximum number of inner-loop iterations needed to attain the convergence of both loops obtained by using the modified and conventional NCCGA to solve the multi-year two-stage ARO TNEP problem at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
Number of outer-loop iterations of the modified NCCGA	1	2	2	2	2
Number of outer-loop iterations of the conventional NCCGA	1	2	1*	1*	2*
Maximum number of inner-loop iterations of the modified NCCGA	2	2	2	2	2
Maximum number of inner-loop iterations of the conventional NCCGA	2	3	3*	3*	3*

\*Problem not solved in less than 100 h.

that the ADA-based initialization of the inner loop was not applied in this case because the algorithm of the CCGA does not involve an inner loop, i.e., the two lowermost optimization levels are recast as an equivalent single-level optimization problem by using the Lagrangian duality theory owing to the lack of second-stage binary decision variables.

Numerical results obtained by using the relaxed approach are shown in Table 6. Observe that the use of the relaxed model leads to estimated total worst-case costs significantly lower than those attained by using the benchmark approach. These underestimations involve an average absolute relative error of the total worst-case cost of 7.57% at the uncertainty levels analyzed. Furthermore, Fig. 11 shows that the investment plans identified by the relaxed approach differ from those attained by the benchmark model. Note that the differences in the number of transmission lines built by using both approaches does not follow a pattern, since the solutions of the relaxed approach involve building more or less transmission lines in comparison with the benchmark results depending on the uncertainty level, and neither do the differences in the time at which the expansion decisions are made. It is, therefore, not easy to infer the optimal investment plan associated with the benchmark approach from the results attained by using the relaxed model.

#### 4.2.3. Impact of storage facilities on the expansion of the transmission network of power systems

We compared the results of the multi-year two-stage ARO TNEP problem obtained by using the benchmark approach described in Section 2 with those attained by considering a modified version

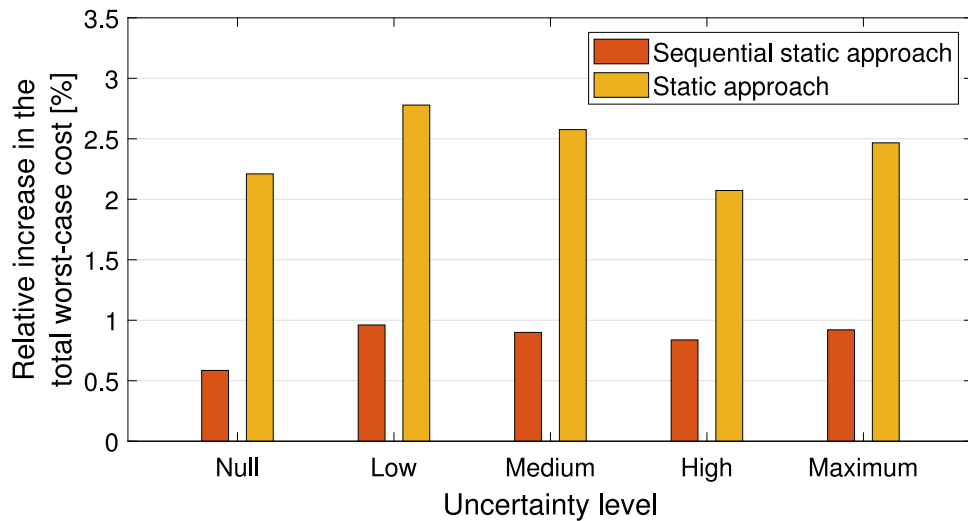


Fig. 8. IEEE 118-bus TS: relative increase in the total worst-case cost obtained by using the sequential static, and static approaches at different uncertainty levels.

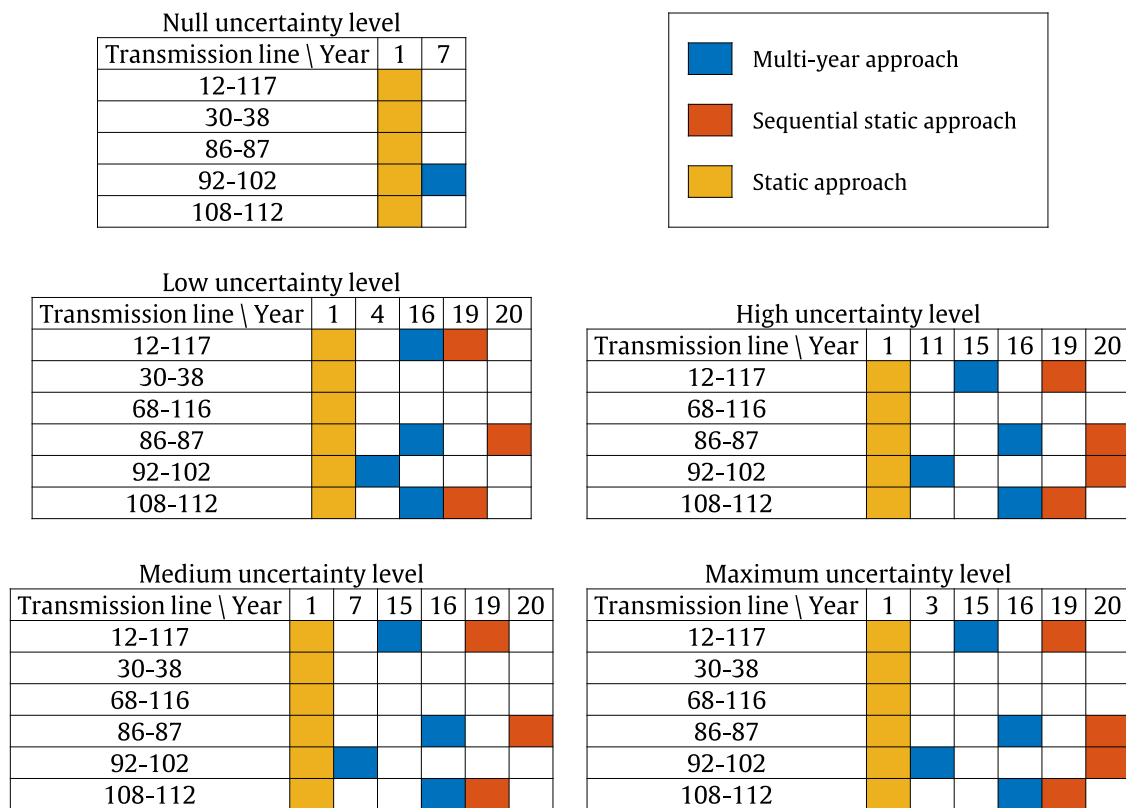


Fig. 9. IEEE 118-bus RTS: investment plan obtained by using the multi-year, sequential static, and static approaches at different uncertainty levels.

of that model in which storage facilities are not considered. Table 7 shows the estimated total worst-case cost and the relative increase in the total worst-case cost obtained by using the model without storage facilities. Numerical results illustrate that the lack of storage facilities in the power system leads to increases in the total worst-case cost between 11% and 25% in comparison with the results obtained by using the benchmark approach. These increases are mainly associated with the production costs of conventional generating units except in the case related to the maximum uncertainty level, in which the rise in the total worst-case cost is also associated with load shedding costs. These results illustrate that storage facilities provide more flexibility to the power

system to minimize the total worst-case cost. Furthermore, Fig. 12 shows that different investment decisions are generally identified by using both approaches.

#### 4.2.4. Sensitivity analyses

Lastly, we performed several sensitivity analyses to assess the impact of the maximum deviations of the uncertain parameters on the total worst-case cost. We solved the multi-year two-stage ARO TNEP problem at the medium uncertainty level by considering different values for these maximum deviations, namely, 1%, 3%, 5%, 7%, and 9% of the forecast values. We carried out the following sensitivity analyses:

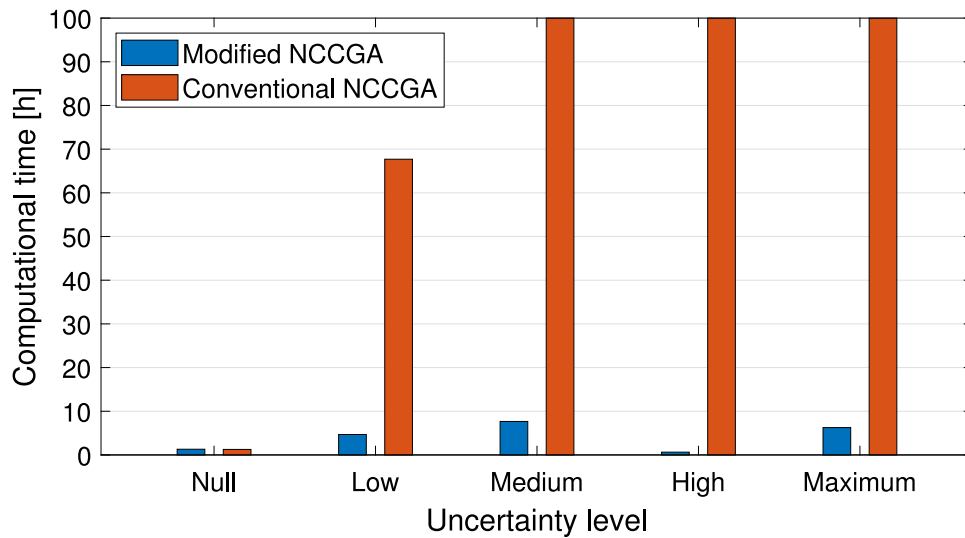


Fig. 10. IEEE 118-bus TS: computational time of the multi-year two-stage ARO TNEP problem obtained by using the modified and conventional NCCGA at different uncertainty levels.

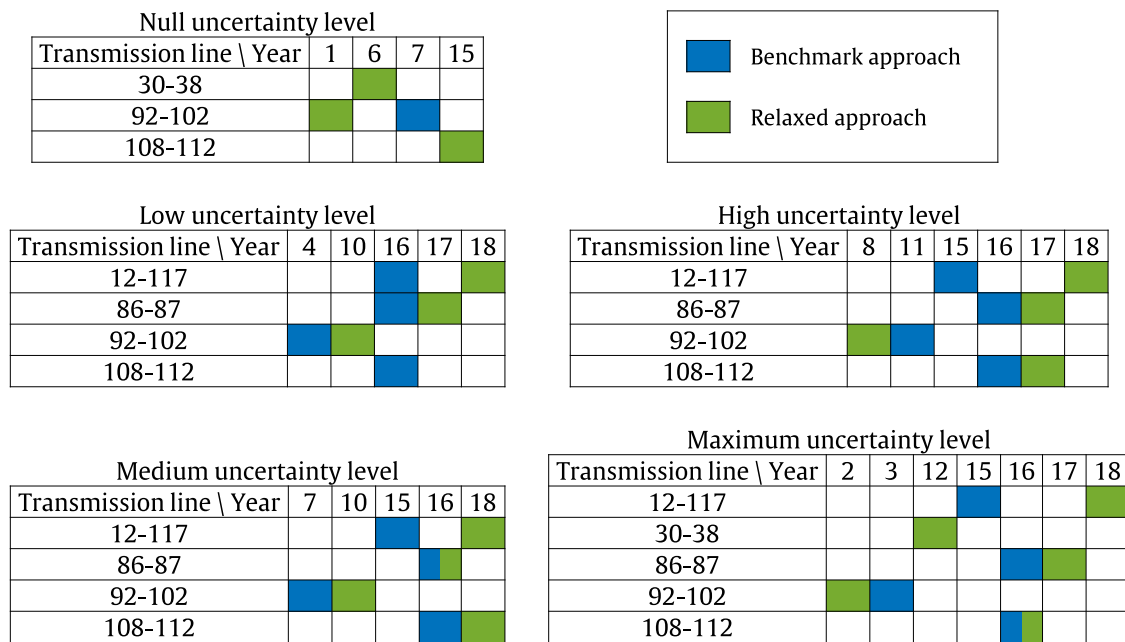


Fig. 11. IEEE 118-bus RTS: investment plan obtained by using the benchmark and relaxed approaches at different uncertainty levels.

Table 6

IEEE 118-bus TS: estimated total worst-case cost and absolute relative error of the total worst-case cost obtained by using the relaxed approach at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
Estimated total worst-case cost [ $10^6$ \$]	1761.88	1969.03	2054.94	2121.02	2167.30
Absolute relative error of the total worst-case cost [%]	8.54	7.53	7.50	7.31	6.96

Table 7

IEEE 118-bus TS: estimated total worst-case cost and relative increase in the total worst-case cost obtained by using the benchmark model without storage facilities at different uncertainty levels.

Uncertainty level	Null	Low	Medium	High	Maximum
Estimated total worst-case cost [ $10^6$ \$]	2157.41	2373.00	2517.23	2735.95	2910.19
Relative increase in the total worst-case cost [%]	12.00	11.44	13.31	19.56	24.93

- Sensitivity analysis A: we considered different values of the maximum increases that the peak power consumption of loads may undergo in their forecast values.

- Sensitivity analysis B: we considered different values of the maximum decreases that the capacity of conventional generating units may undergo in their forecast values.



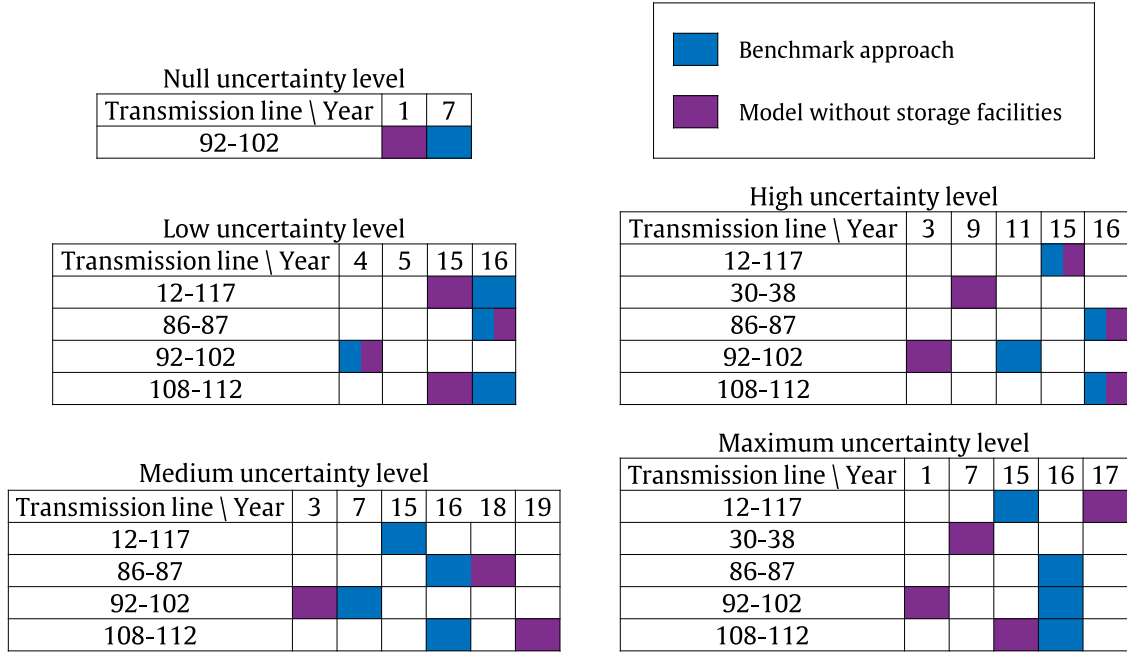


Fig. 12. IEEE 118-bus RTS: investment plan obtained by using the benchmark approach and the model without storage facilities at different uncertainty levels.

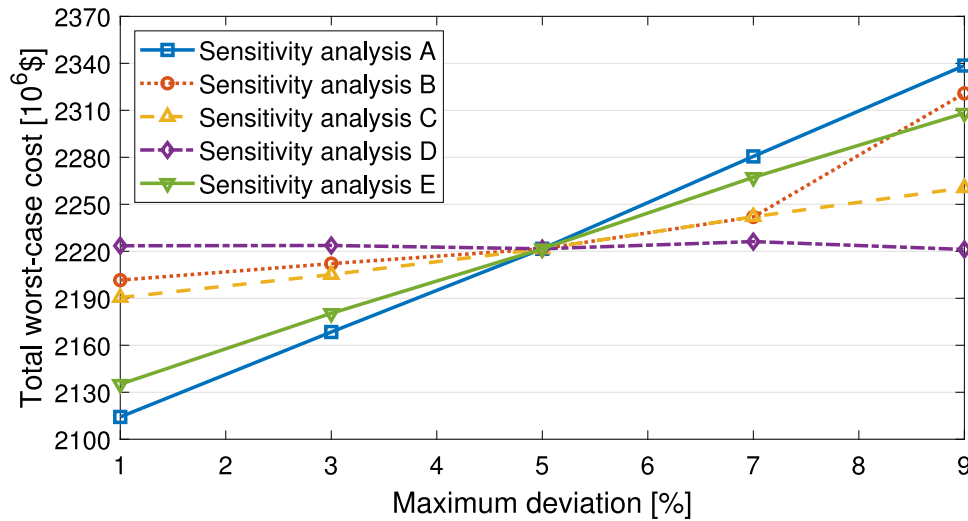


Fig. 13. IEEE 118-bus TS: sensitivity analyses of the total worst-case cost obtained by using the multi-year approach at the medium uncertainty level for different maximum deviations of the uncertain parameters.

- Sensitivity analysis C: we considered different values of the maximum decreases that the capacity of wind-power units may undergo in their forecast values.
- Sensitivity analysis D: we considered different values of the maximum decreases that the capacity of solar-power units may undergo in their forecast values.
- Sensitivity analysis E: we considered different values of the maximum increases that the marginal production cost of conventional generating units may undergo in their forecast values.

The results of these sensitivity analyses are shown in Fig. 13. Observe that the total worst-case cost is increased when the maximum deviations of the uncertain parameters rise. Moreover, the peak power consumption of loads are the uncertain parameters whose maximum deviations most affect the total worst-case cost, followed by the marginal production cost of conventional generating units, and the

capacity of conventional, wind- and solar-power generating units. Note that a maximum absolute relative deviation of the total worst-case cost of approximately 5% is obtained with respect to the results provided in Section 4.2.1. Furthermore, the investment decisions obtained in most of the cases differ from those shown in Fig. 9 for the multi-year approach at the medium uncertainty level. The planner should, therefore, develop a proper analysis to set the maximum deviations that the uncertain parameters may undergo from their forecast values. This is out of the scope of this work, but the reader is referred to [23], in which the authors define the polyhedral uncertainty set by using available data of the uncertain parameters and forecasting tools.

We have also analyzed the multi-year two-stage ARO TNEP problem by considering only a single uncertainty budget  $I$  to limit the total number of uncertain variables that may reach their lower or upper limits. The sum of the different uncertainty budgets previously considered is equal to 34 at the maximum uncertainty level. We have,

**Table 8**

IEEE 118-bus RTS: number of groups of uncertain variables that undergoes deviations from their forecast values in year 20 by using only a single uncertainty budget.

Uncertainty budget, $\Gamma$	7	14	21	28
# groups of loads that undergo increases in their peak power consumption	2	8	11	13
# groups of conventional generating units that undergo decreases in their capacities	2	3	5	6
# groups of wind-power units that undergo decreases in their capacities	1	1	3	4
# groups of solar-power units that undergo decreases in their capacities	0	0	0	1
# groups of conventional generating units that undergo increases in their marginal production costs	2	2	2	4

therefore, analyzed the following values of  $\Gamma$ : 7, 14, 21, and 28. Table 8 shows that most of the groups of uncertain variables that undergo deviations from their forecast values when  $\Gamma$  is equal to 14 are the peak power consumption of loads. This means that the worst-case situation in terms of maximizing the total worst-case cost is mainly driven by the uncertainty in the peak power consumption of loads. The results obtained at greater values of  $\Gamma$  show that more deviations are undergone by the rest of the uncertain variables once the majority of the loads undergoes increases in their peak power consumption. The use of different uncertainty budgets, therefore, provides a fairer approach when the uncertainty in several unknown parameters is analyzed since the deviations undergone are distributed in different sets of uncertain variables.

## 5. Conclusions

This paper presents a new approach for the multi-year two-stage ARO TNEP problem with high penetration of renewable generation. A multi-year approach is considered rather than sequential static and static approaches. ARO is used to identify the worst-case realization of the future uncertain conditions of the power system that maximizes the operating costs, where the uncertain parameters are the peak power consumption of loads, the marginal production cost of conventional generating units, and the capacity of generating units. Moreover, the presence of wind- and solar-power units is considered, and the operational variability of their production levels and the electrical demand is modeled by means of a set of RDs. Certain features associated with the detailed operation of power systems, which are generally ignored in previous multi-year two-stage ARO expansion planning approaches from the technical literature, are simultaneously considered in this work, namely, the commitment statuses and ramping limits of conventional generating units and the non-convex operational feasibility sets of storage facilities. The multi-year two-stage ARO TNEP problem is formulated through a three-level model and it is solved by combining the NCCGA with two exact acceleration techniques. The following statements are inferred from the numerical results of two case studies:

1. Relative increases in the total worst-case cost of up to 7% are obtained when the comprehensive view of the planning horizon is ignored by using static and sequential static approaches rather than a multi-year model for the multi-year two-stage ARO TNEP problem.
2. More transmission lines are usually built when the static approach is applied in comparison with the results of the multi-year model, while the use of the sequential static approach generally leads to delays in the building of new transmission lines in comparison with the results of the multi-year approach.
3. The use of a relaxed model, in which the detailed operation of the power system is not considered, leads to underestimations of the total worst-case cost of over 8%.
4. The flexibility provided by storage facilities involves reductions in the total worst-case cost close to 25%.
5. Particular attention should be paid to the values set to the maximum deviations that the peak power consumption of loads may undergo from their forecast values, since they significantly influence the investment plan.

Finally, some proposals to continue this research are:

- The use of an ellipsoidal uncertainty set to model the correlation among different uncertain parameters. Note that this correlation cannot be modeled by using a cardinality-constrained uncertainty set. Moreover, this framework would allow us to control the conservativeness of the solution through the size of the ellipsoidal uncertainty set.
- The modeling of the power flows through transmission lines by using an AC model rather than the lossless DC model considered in this work.
- The use of a rolling horizon approach to approximate the multi-year multi-stage ARO TNEP problem to a set of multi-year two-stage ARO TNEP problems sequentially solved.

## CRediT authorship contribution statement

**Álvaro García-Cerezo:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luis Baringo:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Raquel García-Bertrand:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data used in the case studies are available in a repository as shown in reference [42] of the manuscript.

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## Appendix. Formulation of the static and sequential static approaches

This appendix explains the changes that should be made in the formulation of the multi-year two-stage ARO TNEP problem described in Section 2 when considering static and sequential static approaches:

- Static two-stage ARO TNEP problem, in which the upper-level problem minimizes the sum of the annualized investment and worst-case operating costs for a target year. The investment costs are, therefore, annualized by using a capital recovery factor, which is computed taking into consideration the interest rate and the investment return period. Moreover, the discount rate is removed from the constraint that imposes the limit on the investment costs since all expansion decisions are made at the beginning of the planning horizon. Furthermore, the forecast values and the maximum deviations of the uncertain parameters are assumed to be equal to those values in the last year of the planning horizon in order to make a fair approximation of the results provided by the multi-year model. The formulation of the lower-level problem is the same as that used in the multi-year approach, but particularized for the target year. The reader is referred to the Appendix of [34] for further information on the detailed formulation of the static two-stage ARO TNEP problem.
- Sequential static two-stage ARO TNEP problem, in which the upper-level problem is solved by considering only one year of the planning horizon. In this case, constraints (1c)–(1e) are replaced with the following constraints for year  $y$ :

$$\sum_{\ell \in \Omega^{L+}} \frac{1}{(1+\kappa)^{y-1}} I_{\ell}^L v_{\ell y}^L \leq \bar{I}^T - \sum_{\ell \in \Omega^{L+}} \sum_{\bar{y}=1}^{y-1} \frac{1}{(1+\kappa)^{\bar{y}-1}} I_{\ell}^L v_{\ell \bar{y}}^L, \quad (\text{A.1a})$$

$$v_{\ell y}^L + \sum_{\bar{y}=1}^{y-1} v_{\ell \bar{y}}^L \leq 1; \quad \forall \ell \in \Omega^{L+}, \quad (\text{A.1b})$$

$$\bar{v}_{\ell y}^L = v_{\ell y}^L + \sum_{\bar{y}=1}^{y-1} v_{\ell \bar{y}}^L; \quad \forall \ell \in \Omega^{L+}, \quad (\text{A.1c})$$

where parameter  $v_{\ell y}^L$  is equal to 1 if candidate transmission line  $\ell$  has been built in previous year  $\bar{y}$ , being otherwise 0. Constraint (A.1a) limits the investment costs by using the difference between the investment budget and the investment costs of previous years. Constraints (A.1b) impose that each candidate transmission line can be built only once. Eq. (A.1c) define the building status of a candidate transmission line. Note that  $v_{\ell y}^L$  is set to the optimal value of variable  $v_{\ell y}^L$  obtained after solving the problem for year  $y$ . Lastly, the formulation of the middle- and lower-level problems do not change with respect to the multi-year approach since they are independently solved for each year.

## References

- [1] Mahdavi M, Antúnez CS, Ajalli M, Romero R. Transmission expansion planning: literature review and classification. *IEEE Syst J* 2019;13(3):3129–40.
- [2] United Nations Framework Convention on Climate Change. The paris agreement. 2023, [Online]. Available: <https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement>.
- [3] European Commission. 2050 Long-term strategy. 2023, [Online]. Available: [https://ec.europa.eu/clima/policies/strategies/2050\\_en](https://ec.europa.eu/clima/policies/strategies/2050_en).
- [4] Quiroga D, Sauma E, Pozo D. Power system expansion planning under global and local emission mitigation policies. *Appl Energy* 2019;239:1250–64.
- [5] Conejo AJ, Baringo L, Kazempour SJ, Siddiqui AS. Investment in electricity generation and transmission: decision making under uncertainty. Cham, Switzerland: Springer International Publishing; 2016.
- [6] Hoffmann M, Kotzur L, Stolten D, Robinus M. A review on time series aggregation methods for energy system models. *Energies* 2020;13(3):641.
- [7] Domínguez R, Vitali S. Multi-chronological hierarchical clustering to solve capacity expansion problems with renewable sources. *Energy* 2021;227:120491.
- [8] Pineda S, Morales JM. Chronological time-period clustering for optimal capacity expansion planning with storage. *IEEE Trans Power Syst* 2018;33(6):7162–70.
- [9] Strbac G, Aunedi M, Konstantelos I, Moreira R, Teng F, Moreno R, et al. Opportunities for energy storage: Assessing whole-system economic benefits of energy storage in future electricity systems. *IEEE Power Energy Mag* 2017;15(5):32–41.
- [10] Poncet K, Delarue E, D'haeseleer W. Unit commitment constraints in long-term planning models: Relevance, pitfalls and the role of assumptions on flexibility. *Appl Energy* 2020;258:113843.
- [11] Cedeño EB, Arora S. Performance comparison of transmission network expansion planning under deterministic and uncertain conditions. *Int J Electr Power Energy Syst* 2011;33(7):1288–95.
- [12] Ben-Tal A, El Ghaoui L, Nemirovski A. Robust optimization. Princeton, NJ, USA: Princeton University Press; 2009.
- [13] Ben-Tal A, Goryashko A, Guslitzer E, Nemirovski A. Adjustable robust solutions of uncertain linear programs. *Math Program* 2004;99(2):351–76.
- [14] García-Bertr R, Mínguez R. Dynamic robust transmission expansion planning. *IEEE Trans Power Syst* 2017;32(4):2618–28.
- [15] Roldán C, Sánchez de la Nieta AA, García-Bertrand R, Mínguez R. Robust dynamic transmission and renewable generation expansion planning: Walking towards sustainable systems. *Int J Electr Power Energy Syst* 2018;96:52–63.
- [16] Haghighat H, Zeng B. Security-constrained robust dynamic power system planning with discrete recourse. *Electr Power Syst Res* 2023;214(part A):108858.
- [17] Chen B, Wang J, Wang L, He Y, Wang Z. Robust optimization for transmission expansion planning: Minimax cost vs. minimax regret. *IEEE Trans Power Syst* 2014;29(6):3069–77.
- [18] Dehghan S, Amjadi N. Robust transmission and energy storage expansion planning in wind farm-integrated power systems considering transmission switching. *IEEE Trans Sustain Energy* 2016;7(2):765–74.
- [19] Zhang X, Conejo AJ. Robust transmission expansion planning representing long- and short-term uncertainty. *IEEE Trans Power Syst* 2018;33(2):1329–38.
- [20] Latorre G, Cruz RD, Areiza JM, Villegas A. Classification of publications and models on transmission expansion planning. *IEEE Trans Power Syst* 2003;18(2):938–46.
- [21] Jabr RA. Robust transmission network expansion planning with uncertain renewable generation and loads. *IEEE Trans Power Syst* 2013;28(4):4558–67.
- [22] Benders JF. Partitioning procedures for solving mixed-variables programming problems. *Numer Math* 1962;4:238–52.
- [23] Ruiz C, Conejo AJ. Robust transmission expansion planning. *European J Oper Res* 2015;242(2):390–401.
- [24] Zeng B, Zhao L. Solving two-stage robust optimization problems using a column-and-constraint generation method. *Oper Res Lett* 2013;41(5):457–61.
- [25] Bertsimas D, Sim M. The price of robustness. *Oper Res* 2004;52(1):35–53.
- [26] Mínguez R, García-Bertrand R. Robust transmission network expansion planning in energy systems: Improving computational performance. *European J Oper Res* 2016;248(1):21–32.
- [27] Arroyo JM, Baringo L, Baringo A, Bolaños R, Alguacil N, Cobos NG. On the use of a convex model for bulk storage in MIP-based power system operation and planning. *IEEE Trans Power Syst* 2020;35(6):4964–7.
- [28] Li Z, Guo Q, Sun H, Wang J. Sufficient conditions for exact relaxation of complementarity constraints for storage-concerned economic dispatch. *IEEE Trans Power Syst* 2016;31(2):1653–4.
- [29] Konno H. A cutting plane algorithm for solving bilinear programs. *Math Program* 1976;11(1):14–27.
- [30] Floudas CA. Nonlinear and mixed-integer optimization: fundamentals and applications. New York, NY, USA: Oxford University Press; 1995.
- [31] Wang S, Geng G, Jiang Q. Robust co-planning of energy storage and transmission line with mixed integer recourse. *IEEE Trans Power Syst* 2019;34(6):4728–38.
- [32] Zhao L, Zeng B. An exact algorithm for two-stage robust optimization with mixed integer recourse problems. Tampa, FL, USA: University of South Florida; 2012, [Online]. Available: [www.optimization-online.org/DB\\_FILE/2012/01/3310.pdf](http://www.optimization-online.org/DB_FILE/2012/01/3310.pdf).
- [33] García-Cerezo Á, Baringo L, García-Bertrand R. Robust transmission network expansion planning considering non-convex operational constraints. *Energy Econ* 2021;98:105246.
- [34] García-Cerezo Á, García-Bertrand R, Baringo L. Acceleration techniques for adaptive robust optimization transmission network expansion planning problems. *Int J Electr Power Energy Syst* 2023;148:108985.
- [35] Rintamäki T, Oliveira F, Siddiqui AS, Salo A. Achieving emission-reduction goals: multi-period power-system expansion under short-term operational uncertainty. *IEEE Trans Power Syst* 2023. <http://dx.doi.org/10.1109/TPWRS.2023.3244668>, [in press].
- [36] Binato S, Pereira MVF, Granville S. A new Benders decomposition approach to solve power transmission network design problems. *IEEE Trans Power Syst* 2001;16(2):235–40.
- [37] IBM. CPLEX Optimizer. 2023, [Online]. Available: <https://www.ibm.com/analytics/cplex-optimizer>.
- [38] Rosenthal RE. GAMS - A user's guide. Washington, DC, U.S.: GAMS Development Corporation; 2007.
- [39] García-Cerezo Á, García-Bertrand R, Baringo L. Enhanced representative time periods for transmission expansion planning problems. *IEEE Trans Power Syst* 2021;36(4):3802–5.
- [40] García-Cerezo Á, García-Bertrand R, Baringo L. Priority chronological time-period clustering for generation and transmission expansion planning problems with long-term dynamics. *IEEE Trans Power Syst* 2022;37(6):4325–39.

- [41] García-Cerezo Á, García-Bertrand R, Baringo L. Computational performance enhancement strategies for risk-averse two-stage stochastic generation and transmission network expansion planning. *IEEE Trans Power Syst* 2023. <http://dx.doi.org/10.1109/TPWRS.2023.3236397>, [in press].
- [42] García-Cerezo Á, Baringo L, García-Bertrand R. Expansion planning of the transmission network with high penetration of renewable generation: a multi-year two-stage adaptive robust optimization approach. Data for the case studies, Mendeley Data. 2023, [Online]. Available: <https://doi.org/10.17632/pj5gzdyj9v.1>.
- [43] Grigg C, Wong P, Albrecht P, Allan R, Bhavaraju M, Billinton R, et al. The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee. *IEEE Trans Power Syst* 1999;14(3):1010–20.
- [44] Peña I, Martínez-Anido CB, Hodge B. An extended IEEE 118-bus test system with high renewable penetration. *IEEE Trans Power Syst* 2018;33(1):281–9.