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Achieving Emission-Reduction Goals: Multi-Period Power-System Expansion under Short-Term Operational Uncertainty

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Abstract—Stochastic adaptive robust optimization is capable of handling short-term uncertainties in demand and variable renewable-energy sources that affect investment in generation and transmission capacity. We build on this setting by considering a multi-year investment horizon for finding the optimal plan for generation and transmission expansion while reducing greenhouse gas emissions. In addition, we incorporate multiple hours in power-system operations to capture hydropower operations and flexibility requirements for utilizing variable renewable energy sources such as wind and solar power. To improve the computational performance of existing exact methods for this problem, we employ Benders decomposition and solve a mixed-integer quadratic programming problem to avoid computationally expensive big-M linearizations. The results for a realistic case study for the Nordic and Baltic region indicate which investments are required for reducing greenhouse gas emissions. Through out-of-sample experiments, we show that the stochastic adaptive robust model leads to lower expected costs than a stochastic model.

Index Terms—Emission reduction, generation and transmission expansion, robust optimization, stochastic programming. Benders decomposition

NOMENCLATURE

Indices

\( n/u/\ell \) node/generation unit/transmission line
\( o \) operating condition
\( t/\tau \) time step in the master problem/subproblem
\( i/k \) iteration in the column-and-constraint algorithm/Benders decomposition

Sets

\( \Psi_{G/L} \) existing generation units/transmission lines
\( \Psi_{G,H/L,AC} \) existing hydropower units/alternating current (AC) transmission lines

Parameters

\( P \) scaling factor to make investment and operation costs comparable
\( W_o \) weight of operating condition \( o \)
\( D \) demand growth factor
\( \bar{D}/\hat{D}_o,\tau,n \) nominal demand/demand increase at node \( n \) in condition \( o \) in period \( \tau \) (MWh)
\( E_t \) \( \text{CO}_2 \) emission target in period \( t \) (tonne)
\( R \) discount factor
\( C_{t,u}^o \) investment cost of candidate unit \( u \) in period \( t \) (€/MW)
\( C_{t,\ell}^o \) investment cost of building candidate transmission line \( \ell \) in period \( t \) (€)
\( C_{o,\tau,u}^o \) generation cost of unit \( u \) in condition \( o \) in period \( \tau \) (€/MWh)
\( A_{o,\tau,u} \) availability of unit \( u \) in condition \( o \) in period \( \tau \) (%)
\( X_u \) maximum invested capacity in candidate unit \( u \) (MW)
\( \bar{G}_{o,\tau,u} \) maximum generation of unit \( u \) in condition \( o \) in period \( \tau \) (MWh)
\( \bar{G}/\hat{G}_{o,\tau,u} \) maximum ramp up/ramp down of unit \( u \) in condition \( o \) in period \( \tau \) (MW)
\( \bar{G}_c, S^c_{o,\tau,u} \) \( \text{CO}_2 \) emission rate of unit \( u \) (tonne/MWh)
initial storage level of hydropower unit \( u \) in condition \( o \) in period \( \tau \) (MWh)
\( S/S_o,\tau,u \) maximum/minimum final storage level of hydropower unit \( u \) in condition \( o \) in period \( \tau \) (MWh)
\( I_{o,\tau,u} \) inflow to hydropower unit \( u \) in condition \( o \) in period \( \tau \) (MWh)
\( \bar{F}/\hat{F}_{o,\tau,\ell} \) maximum/minimum flow on line \( \ell \) in condition \( o \) in period \( \tau \) (MW)
\( B_{\ell} \) susceptance of line \( \ell \) (S)
\( \Lambda^w \) demand uncertainty budget
I. INTRODUCTION

Most nations have ratified the Paris Agreement that aims at capping the increase in the global average temperature by lowering greenhouse gas (GHG) emissions [1]. To this end, there are national policies that set specific goals for GHG emission reductions through measures such as increasing energy efficiency and the share of renewable energy of total energy consumption [2]. Due to the limited availability of dispatchable renewable-energy sources (RES) such as hydropower and biomass, investments in non-dispatchable variable RES (VRES), such as wind and solar power, are required. However, integrating substantial VRES capacities in existing power systems is likely to require significant investments in transmission capacity as well as flexible generation technologies (e.g., combined cycle gas turbines, CCGT) and storage to guarantee power-system adequacy and security [3].

Given this background, we consider the generation and transmission expansion planning (G&TEP) problem, i.e., the required infrastructural expansions, e.g., transmission line, VRES, and other generation, for meeting long-term GHG emission-reduction goals. We require meeting short-term operational constraints on demand, transmission, generator ramping, and availability taking into account related uncertainties and the decision maker’s robustness requirements. Thus, we employ a two-stage robust optimization model that can be formulated as a tri-level model, in which the first stage and level consider a multi-year investment horizon for generation and transmission expansion. At the second stage, the second level uses robust optimization (RO) to choose a worst-case demand for the third level that uses stochastic programming (SP) to minimize the cost of detailed, multi-hour power-system operation under a set of operating conditions (scenarios) for uncertain parameters such as VRES output and generation costs. We choose demand as the uncertain variable at the second level as it is a key driver for the long-term uncertainty of investment decisions and generation adequacy, which are the foremost interests of our analysis. Meanwhile, at the third level, we capture short-term, hourly operational uncertainties. This combination of RO and SP in two stages is called stochastic adaptive robust optimization (SARO) [4]. We apply the framework to a realistic case study covering Denmark, Estonia, Finland, Latvia, Lithuania, Norway, and Sweden.

The two-stage robust optimization problems, also known as SARO problems, for G&TEP are computationally challenging. [5] combine the best features of earlier exact solution algorithms to develop a more effective solution method based on the column-and-constraint (CC) algorithm in which solving the first-level and the second- as well as third-level problems alternate until their costs match. These alternating problems are called the master problem and subproblem, respectively. In the context of G&TEP, the master problem is a mixed-integer linear program (MILP) and the subproblem is a mixed-integer non-linear problem (MINLP), which can be reformulated as a computationally expensive MILP using a big-M-based
linearity. To this end, [6] develop an approximate block coordinate descent method to avoid the expensive linearization of the subproblem. Other inexact solution methods involve metaheuristics such as genetic algorithms [7]. However, in this paper, we note that the subproblem is a mixed-integer quadratic program (MIQP), which can be solved faster than the linearized MILP using modern solvers such as Gurobi [8]. The MIQP solution method removes the need for additional constraints and parameters, which facilitates its application to other bi-level model instances, too. Moreover, we profile the CC algorithm and note that the master problem is a computational bottleneck as its size increases at every CC iteration. Consequently, we employ Benders decomposition [9] to break up the large MILP master problem into a small MILP and a large linear program (LP), which are faster to solve for large problem instances and lend themselves to parallelization. Accelerating the CC master problem allows us to solve larger problem instances faster and with less computational resources. To the best of our knowledge, our paper is the first one to accelerate the CC master problem in the SARO setting.

The two-stage robust optimization framework is employed for the G&TEP problem in [4], [5], and [10] but without the multi-year and multi-hour time dimensions and a goal for GHG emission reduction. [11] and [12] consider multiple years, but they do not focus on GHG emission reduction, do not model storage or hydropower, and do not provide an accelerated solution method for the master problem. [13] and [14] consider multiple years, but they do not use either a GHG emission-reduction goal or an accelerated solution method for the master problem. Also, the G&TEP problem has been studied extensively in single- ([15]–[17]) and bi-level settings ([18]–[20]), but these do not employ RO as an uncertainty modeling framework. Consequently, our SARO model for the G&TEP problem extends the state of the art to enable us to solve for large problem instances faster and with less computational resources. Other inexact solution methods involve metaheuristics such as genetic algorithms [7]. However, in this paper, we note that the subproblem is a mixed-integer quadratic program (MIQP), which can be solved faster than the linearized MILP using modern solvers such as Gurobi [8].

Given this context, the contributions of this paper are:

C1) To consider multi-year and multi-hour time scales as well as detailed power-system operations, e.g., hydropower and a constraint for GHG emissions, in a SARO problem for G&TEP.

C2) To improve the solution time of earlier exact methods by applying Benders decomposition to the master problem and by solving the subproblem as an MIQP. Using MIQP removes the need for the expensive big-M linearization used in earlier work.

C3) To show which investments in transmission, wind power, and flexible generation capacity are required for reducing GHG emissions in a centrally planned system using a realistic case study for Nordic and Baltic countries. We show that these investments are robust to changes in uncertainty parameters with a preference for wind power at higher uncertainty levels.

C4) Through out-of-sample comparisons, to lay bare how investment plans obtained using an SP model or a model with less detailed power-system operations would not be able to cope with random load changes under increasingly stringent environmental considerations. By contrast, a SARO-based investment plan would mitigate the severest economic consequences by adopting more VRES generation.

The remainder of this paper is organized as follows. Section II presents the mathematical formulation of our SARO problem, and Section III details our solution methods. Section IV presents the results from a realistic case study. Finally, Section V summarizes and provides future research directions.

II. PROBLEM DESCRIPTION

At the 1st stage and level of the SARO G&TEP problem, we consider a central planner that makes an expansion plan in a long-term horizon consisting of time steps $t$ that we interpret as years. While doing this, the central planner considers the 2nd stage, where the 2nd level chooses the worst-case demand so as to maximize power-system operation costs. Also, at the 2nd stage, the central planner considers the 3rd level in which a market operator minimizes the operational costs in multiple operating conditions $o$ and time steps $\tau$ for each 1st level time step $t$ given the worst-case demand determined by the 2nd level. In order to capture the intraday demand and VRES generation profile, we model power-system operations within each 1st level time step $t$ using a number of 3rd level time steps $\tau$ that we interpret as hours. To model several different intraday demand and VRES generation profiles, we consider multiple operating conditions $o$ at the 3rd level. In addition to minimizing operational costs, the driver for the expansion plan is an upper bound for emissions in each 1st level time step.
A combination of RO and SP is used for modeling uncertainty when making the expansion plan. Following [4], we use RO at the 2nd level to identify the worst-case realization for the demand level. The demand level is seen as a long-term uncertainty that is affected by economic development and electrification of different sectors, for example. The demand level and its uncertainty are key drivers for investment decisions and generation adequacy. The demand-level uncertainty is controlled using an uncertainty budget. On the other hand, following [4] (and other references, e.g., [15], [16], [31]), we use an SP-based formulation that simultaneously considers multiple operating conditions and their respective weights (which are analogous to scenarios and probabilities, respectively) at the 3rd level to model uncertain parameters such as the short-term variability of VRES generation, demand, conventional generation capacities and costs, transmission capacities, and hydro inflows. To capture the short-term variability of demand and VRES generation, i.e., their intraday profiles, we define multiple operating conditions o and 3rd level time steps τ within each 1st level time step t. These intraday profiles are sampled from real power-system data using the hierarchical clustering method of [33]. In addition, we represent short-term uncertainty in conventional generation capacities and costs, transmission capacities, and hydro inflows by sampling from a probability distribution in each operating condition o and 3rd level time step τ.

A. Model formulation

In the following, Ω denotes the uncertainty set from which the worst-case demand is selected and ξ denotes the feasibility set for the operational decisions once the 1st and 2nd level decisions have been made. The mathematical formulation for our SARO G&TEP problem is:

\[
\begin{align*}
\min_{\Phi} & \quad P \sum_t R^{-t} \left[ \sum_{u \in \Psi^{G+}} C^r_{t,u} \hat{x}_{t,u} + \sum_{\ell \in \Psi^{L+}} C^g_{t,\ell} \hat{y}_{t,\ell} \right] \\
\text{s.t.} & \quad x_{t,u} = \sum_{\ell=1}^t \hat{x}_{t',u} \quad \forall t, u \in \Psi^{G+} \\
& \quad y_{t,\ell} = \sum_{\ell=1}^\tau \hat{y}_{t',\ell} \quad \forall t, \ell \in \Psi^{L+} \\
& \quad x_{t,u} \leq X_u \quad \forall t, u \in \Psi^{G+},
\end{align*}
\]

where

\[
\Phi^L = \{ x_{t,u}, x_{t,u}, \forall u \in \Psi^{G+}, y_{t,\ell}, y_{t,\ell}, \forall t, \ell \in \Psi^{L+} \}, \forall t,
\]

\[
\Phi^L = \{ d_{o,\tau,n}, o, \tau, w_n \}, \forall n, \text{ and } \Phi^L = \{ g_{o,\tau,u}, o, \tau, u; \}
\]

\[
s_{o,\tau,u}, o \in \Psi^{G,H}; f_{o,\tau,\ell}, o, \tau, \ell; \delta_{o,\tau,n}, o, \tau, n; \forall o, \tau, \forall n.
\]

In the objective function (1), the first minimization problem represents the generation and transmission expansion costs (1st level), and the maximization problem represents the selection of the worst-case demand (2nd level) for the second minimization problem of attaining the least-cost power-system operations (3rd level). The parameter P is used to annualize the expansion costs to make them comparable with operational costs. Constraints (2) and (3) define the capacities of candidate units and transmission lines that are available at each 1st level time step t, respectively. Constraints (4) define maximum investments in the new generation units.

Following [5] and [4], the uncertainty set Ω is given by:

\[
\{ d_{o,\tau,n} = D^{(o)}(\tau), D_{o,\tau,n} + w_n D_{o,\tau,n} \} \forall o, \tau, n
\]

(5)

\[
\sum_n w_n \leq \Lambda w
\]

(6)

Eq. (5) defines that the demand is equal to the sum of nominal demand \( \tilde{D}_{o,\tau,n} \) and a possible demand increase \( D_{o,\tau,n} \) multiplied by demand growth factor \( D \) that compounds at each 1st level time step \( t \). The demand increase is selected using binary variables \( w_n \) in an attempt to maximize the operation costs. Eq. (6) sets an uncertainty budget on the number of demand increases the 2nd level model can activate.

For formulating power-system operations in Eqs. (7)-(20), we define \( n(u) \) as the node at which unit \( u \) is located. Also, the notation \( t \in \tau \) indicates the 3rd level time steps \( \tau \) within a 1st level time step \( t \), and an inverse mapping \( t(\tau) \) gives the 1st level time step \( t \) that the 3rd level time step \( \tau \) belongs to. The definition of the two different time scales and the related sets are shown in Figure 1. Consequently, given the optimal values \( x_{t',u}, y_{t,\ell} \in \Psi^{G+}, y_{t,\ell} \in \Psi^{L+}, D_{o,\tau,n}, \forall o, \tau, n, \) the feasibility set \( \Xi(g_{o,\tau,u}, s_{o,\tau,u}, f_{o,\tau,\ell}, \delta_{o,\tau,n}) \) is:

\[
\left\{ \begin{array}{l}
\sum_t g_{o,\tau,u} + \sum_{\ell \in \Psi^{L+}} f_{o,\tau,\ell} + \\
0 \leq g_{o,\tau,u} \leq A_{o,\tau,u} G_{o,\tau,u} \forall o, \tau, u \in \Psi^{G+} \\
0 \leq g_{o,\tau,u} \leq A_{o,\tau,u} x_{t,\tau}(u) \forall o, \tau, u \in \Psi^{G+} \\
G_{o,\tau,u} \leq g_{o,\tau+1,u} - g_{o,\tau,u} \forall o, \tau, u \in T_r, u \\
g_{o,\tau+1,u} - g_{o,\tau,u} \leq G_{o,\tau,u} \forall o, \tau, u \in T_r, u \\
s_{o,\tau,u} \geq 0 \forall o, \tau, u \in \Psi^{G,H} \\
s_{o,\tau,u} = s_{0,\tau,u} \forall o, \tau \in T^0, u \in \Psi^{G,H} \\
s_{o,\tau+1,u} = s_{o,\tau,u} - g_{o,\tau,u} + I_{o,\tau,u} \forall o, \tau \in T^r, u \in \Psi^{G,H} \\
S_{o,\tau,u} \leq S_{o,\tau,u} \leq S_{0,\tau,u} \forall o, \tau \in T^{-1}, u \in \Psi^{G,H} \\
f_{o,\tau,\ell} = B_d(\delta_{o,\tau,n} - \delta_{o,\tau,n}(\ell)) \forall o, \tau, \ell \in \Psi^{L^+} \\
E_{o,\tau,\ell} \leq f_{o,\tau,\ell} \leq E_{o,\tau,\ell} \forall o, \tau, \ell \in \Psi^{L^+} \\
E_{o,\tau,\ell} \leq f_{o,\tau,\ell} \leq E_{o,\tau,\ell} \forall o, \tau, \ell \in \Psi^{L^+} \\
\forall o, \tau, \ell \in \Psi^{L^+} \\
\delta_{o,\tau,0} = 0 \forall o, \tau \\
\sum_t \sum_{\tau \in \tau} W_{o} G_{o,\tau,u} \leq E_{t} \forall o, \tau, u
\end{array} \right\}
\]

(7)

(8)

(9)

(10)

(11)

(12)

(13)

(14)

(15)

(16)

(17)

(18)

(19)

(20)

(21)

Eq. (7) requires that the (possibly worst-case) demand is equal to the generation and exchange at each node. Eqs. (8) and (9) impose that the generation of each unit is non-negative.
but less than or equal to the product of the unit’s availability
\(A_{o,\tau,u}\) and the maximum capacity of an existing unit \(G_{o,\tau,u}\)
or the built capacity of a candidate unit \(x_{t,\tau,u}^*\), respectively. Moreover, the generation is limited by ramping constraints (10) and (11).

Following [34], we assume that each hydropower unit has one reservoir that can act as storage. Eq. (12) imposes that storage levels are non-negative. Eq. (13) sets the initial storage level at the first 3rd level time step \(\tau\) within each 1st level time step \(t\). Eq. (14) defines the storage level at the following time step \(\tau + 1\) as the current storage plus the difference of hydropower generation \((g_{o,\tau,u}, u \in \Psi^{G,H})\) and inflows \((I_{o,\tau,u})\) at \(\tau\). To avoid possible storage depletion, Eq. (15) requires that the storage level at the last 3rd level time step \(\bar{S}_{o,\tau,u}\) is within desired levels \(\underline{S}_{o,\tau,u}\) and \(\bar{S}_{o,\tau,u}\). We do not model the link between the final and initial storage levels as these time steps may correspond to representative days many weeks or months apart. Using exogenous values for the initial storage levels reduces the risk of making hydropower too flexible where it could carry too much water between the representative days. As we show in Section IV-E, this hydropower model is more realistic than assuming that hydropower is fully flexible [35], [36]. However, this model does not consider the time value of water or additional constraints imposed by river systems, for example.

The transmission network is represented by alternating current (AC) and direct current (DC) circuits in Eqs. (16)–(20). For AC lines, the transmission flow is determined by Eq. (16). However, flows in existing and candidate transmission lines must be within the capacities of the lines as given by Eqs. (17) and (18), respectively. Related to the AC circuit, the voltage angles at each node and a reference voltage angle are given by Eqs. (19) and (20), respectively.

Finally, Eq. (21) determines the upper bound for CO₂ emissions, which we use as a proxy for GHG emissions, at each 1st level time step \(t\). This constraint applies to the entire region considered, which allows the model to optimize investments based on renewable generation across the region, for example. The framework allows for other criteria such as a country-wise emissions caps or a lower bound on renewable power generation.

In the above formulation, we have assumed that all candidate transmission lines are DC lines for which flow is determined in the power exchange. This is because we focus on emission reduction and VRES integration using cross-border transmission, which is typically implemented via high-voltage DC (HVDC) lines to minimize heat and other relevant losses. However, the above formulation can readily be extended to cover candidate AC lines, too.

III. SOLUTION METHOD

Following [5], the problem (1)–(4) is solved using a column-and-constraint (CC) algorithm in which solving the first minimization problem of (1) and solving the max-min problem of (1) alternates. These two problems are called CC master problem and CC subproblem, respectively. The alternation terminates when the total costs computed from the two problems match indicating the convergence of the method. The formulations for CC master problem and subproblem are given in the following subsections (Eqs. (22)–(39) and Eqs. (40)–(45), respectively) and the solution algorithm is described in detail in Algorithm 1.

### A. CC master problem

At iteration \(\nu\), we have \(\Omega^M = \{g_{o,\tau,u,u'}, \forall u; s_{o,\tau,u,u'}, \forall u \in \Psi^{G,H}; f_{o,\tau,\ell,u'}, \forall \ell; d_{o,\tau,\ell,u'}, \forall u\}, \forall o, \tau, u, u', \forall \nu \leq \nu\). Given \(d_{o,\tau,\ell,u,u'}\), \(\forall o, \tau, u, u' \leq \nu\) as input data obtained from all the previous solutions of the subproblem, the master problem at iteration \(\nu\) is:

\[
\min \sum_{\Phi L,1,\theta} P_t \sum_{t} R^{-t} \left[ \sum_{u \in \Psi^{G+}} C^t_{u,\tau,u} x_{t,\tau,u} + \sum_{\ell \in \Psi^{L+}} C^y_{\ell,\ell} y_{t,\ell} \right] + \theta
\]

s.t.
Eqs. (2) – (4)  
\[ \theta \geq \sum_{o} W_o \sum_{\tau} R^{-t}(\tau) \sum_{u} C_{g, o, \tau, u, \nu} \forall \nu' \leq \nu \] 
\[ \sum_{u}(n(u)=n) g_{o, \tau, u, \nu'} - \sum_{\ell(\tau)=n} f_{o, \tau, \ell, \nu'} + \sum_{\ell(\tau)=n} f_{o, \tau, \ell, \nu'} = d_{o, \tau, n, \nu'} \forall o, \tau, n, \nu' \leq \nu \] 
\[ \sum_{\tau(\tau')=n} \sum_{o} W_{o} G_{o, \tau, u, \nu'} \leq E_{\ell} \forall o, \tau, \nu' \leq \nu \] 
\[ s_{o, \tau, u, \nu'} \geq 0 \forall o, \tau, u \in \Psi^{G,H}, \nu' \leq \nu \] 
\[ s_{o, \tau, u, \nu'} = S_{o, \tau, u} \forall o, \tau \in T^{0}, u \in \Psi^{G,H}, \nu' \leq \nu \] 
\[ s_{o, \tau, u, \nu'} = s_{o, \tau, u, \nu'} - g_{o, \tau, u, \nu'} + I_{o, \tau, u} \forall o, \tau \in T^{r}, u \in \Psi^{G,H}, \nu' \leq \nu \] 
\[ S_{o, \tau, u} \leq s_{o, \tau, u, \nu'} \leq S_{o, \tau, u} \forall o, \tau \in T^{-1}, u \in \Psi^{G,H}, \nu' \leq \nu \] 
\[ f_{o, \tau, \ell, \nu'} = B_{\ell}(\delta_{o, \tau, l}(t), \nu') \forall o, \tau, \ell \in \Psi^{LAC}, \nu' \leq \nu \] 
\[ E_{o, \tau, \ell} \leq f_{o, \tau, \ell, \nu'} \leq E_{o, \tau, \ell} \forall o, \tau, \ell \in \Psi^{L}, \nu' \leq \nu \] 
\[ E_{o, \tau, \ell} y_{l}(t), \ell \leq f_{o, \tau, \ell, \nu'} \leq E_{o, \tau, \ell} y_{l}(t), \ell \forall o, \tau, \ell \in \Psi^{L+}, \nu' \leq \nu \] 
\[ -\pi \leq \delta_{o, \tau, n, \nu'} \leq \pi \forall o, \tau, n, \nu' \leq \nu \] 
\[ \delta_{o, \tau, 0, \nu'} = 0 \forall o, \tau, \nu' \leq \nu \] 

B. CC subproblem

For the subproblem, we define the following:

\[ \Omega^{S} = \{ \beta_{o, \tau, n}, \beta_{o, \tau, u}, \beta_{o, \tau, u}^{r}, d_{o, \tau, n} \}, \forall o, \tau, u \cup \beta^{r}, \forall \ell \cup \{ \phi_{0}^{0, o, \tau, u}, \forall \tau \in T^{0}, \phi_{o, \tau, u}^{r}, \forall \tau \in T^{r}; \phi_{t}^{0, o, \tau, u}^{r}, \forall \tau \in T^{-1}; \phi_{o, \tau, u}^{r}, \forall \tau \in T^{r}, \phi_{o, \tau, u}^{r}, \forall \tau \in T^{r} \} \cup \{ \mu_{o, \tau, \ell}, \mu_{o, \tau, \ell}^{r}, \mu_{o, \tau, \ell}^{v}, \forall o, \tau, \ell \cup \{ \lambda_{o, \tau, n}, \lambda_{o, \tau, n}^{r}, \lambda_{o, \tau, n}^{v}, \forall o, \tau, n \cup \mu_{o, \tau, \ell}^{ref}, \forall o, \tau \} \] 

With \( x_{o, \tau, n, \nu'}, \forall o, \tau, u \in \Psi^{G} \) and \( y_{o, \tau, \ell}, \forall \ell \in \Psi^{L} \) as input data obtained from the previous solution to the master problem, the subproblem is:

\[ \max \phi_{o, \tau, n, \nu'}, \phi_{o, \tau, u}^{r}, \phi_{o, \tau, u}^{r}, d_{o, \tau, n} \] 
\[ \sum_{o} W_{o} \sum_{\tau} R^{-t}(\tau) \sum_{u} C_{g, o, \tau, u, \nu'} \forall \nu' \leq \nu \] 
\[ \sum_{u}(n(u)=n) g_{o, \tau, u, \nu'} - \sum_{\ell(\tau)=n} f_{o, \tau, \ell, \nu'} + \sum_{\ell(\tau)=n} f_{o, \tau, \ell, \nu'} = d_{o, \tau, n, \nu'} \forall o, \tau, n, \nu' \leq \nu \] 
\[ \sum_{\ell(\tau)=n} (\mu_{o, \tau, \ell} - \mu_{o, \tau, \ell}^{r}) \prod^{r}_{r} E_{o, \tau, \ell} \] 
\[ \sum_{\ell(\tau)=n} (\mu_{o, \tau, \ell} - \mu_{o, \tau, \ell}^{r}) y_{l}(t), \ell \] 
\[ \sum_{n} \pi (\mu_{o, \tau, n}^{v} + \mu_{o, \tau, n}^{r}) \] 

\[ \sum_{\tau(\tau')=n} \sum_{o} W_{o} G_{o, \tau, u, \nu'} \leq E_{\ell} \forall o, \tau, \nu' \leq \nu \] 

\[ \sum_{\tau(\tau')=n} \sum_{o} W_{o} G_{o, \tau, u, \nu'} \leq E_{\ell} \forall o, \tau, \nu' \leq \nu \] 

\[ \lambda_{o, \tau, n, \nu'}, \beta_{o, \tau, u}^{r}, + \beta_{o, \tau, u}^{r}, + 1_{\tau \in T_{-1}} = \] 

\[ \sum_{o} \sum_{\tau \in T_{-1}} \phi_{o, \tau, u}^{r} \beta_{o, \tau, u}^{r} = \] 

\[ \sum_{o} \sum_{\tau \in T_{-1}} \phi_{o, \tau, u}^{r} \beta_{o, \tau, u}^{r} = \]
once fixed, render an LP problem. Thus, the Benders master problem at iteration \( k \) of the Benders decomposition chooses \( \Phi_{L1,BM} = \{ y_{t,\ell}, \tilde{y}_{t,\ell}, \forall t, \ell \in \Psi^{\ell+} \} \) by solving the following problem given \( d^*_{0,\tau,n,\nu} \) from the CC subproblem:

\[
\min_{\Phi_{L1,BM}, \eta} P \sum_t R^{-t} \sum_{\ell \in \Psi^{\ell+}} C_{t,\ell}^y \tilde{y}_{t,\ell} + \eta
\]

s.t.

\[
\begin{align*}
\eta - \sum_o \sum_\tau \sum_\nu \left[ \sum_{u \in \Psi} \left( A_{o,\tau,u} \tilde{G}_{0,\tau,u} \tilde{b}_{0,\tau,u,\nu} + \right. \right. \\
\left. \left. \sum_{\ell \in \Psi^{\ell+}} y_{t(\ell)}, \ell \left( F_{0,\tau,\ell} \tilde{\mu}_{0,\tau,\ell,\nu} - \right. \right. \\
\left. \left. \sum_{n} d^*_{0,\tau,n,\nu} \sigma_{0,\tau,n,\nu} + \sum_{o} \pi \left( \tilde{\mu}^0_{o,\tau,n,\nu} + \tilde{L}^0_{o,\tau,n,\nu} \right) + \\
\sum_{u \in \Psi^G,H} \left( \hat{1}_{T^{T^0} I_{o,\tau,u} \phi_{0,\tau,u,\nu} + \right. \right. \\
\left. \hat{1}_{T^{T^{-1}}} ( S_{0,\tau,u} \phi_{0,\tau,u,\nu} - S_{0,\tau,u} \phi^0_{0,\tau,u,\nu} ) \right) \right. \\
\left. \left. - \sum_t \sum_{\ell} x_{t,\ell} \geq 0. \right. \right. \right.
\end{align*}
\]

With \( y_{t^*,\ell^*,k} \) and \( \tilde{y}_{t^*,\ell^*,k} \) as input data, the Benders subproblem at the iteration \( k \) of the Benders decomposition is then given by \( \Phi_{L1,BS} = \{ x_{t,u}, \hat{x}_{t,u}, \forall t, \ell \in \Psi^{\ell+} \} \)

\[
\begin{align*}
\min_{\Phi_{L1,BS}, \Omega, \theta} P \sum_t R^{-t} \left[ \sum_{u \in \Psi^G} C_{0,n}^x \hat{x}_{t,u} + \sum_{\ell \in \Psi^{\ell+}} C_{t,\ell}^x y_{t,\ell}^* \right] + \theta
\end{align*}
\]

s.t.

1st level constraints (2) and (4)

3rd level constraints (24)-(36), (38), and (39)

\[
E_{o,\tau,\ell} ( \hat{y}_{t(\ell)}, \ell, k ) \leq \hat{F}_{o,\tau,\ell,\nu} \leq \tilde{F}_{o,\tau,\ell} \hat{y}_{t(\ell)}, \ell, k \forall o, \tau, \ell \in \Psi^{\ell+}, \nu \leq \nu.
\]

The Benders master problem and subproblem are solved in an alternating fashion until their objective values are within a tolerance \( \epsilon = 10^{-6} \) from each other.

IV. CASE STUDY: TEN-YEAR INVESTMENT PLAN FOR MODIFIED NORDIC AND BALTIC NETWORK

We have made the data and code for our case studies available at https://github.com/tuomas/robust-dev.

A. Data

In order to examine a robust G&TEP plan with a target for CO\(_2\) emissions, we use the Nordic and Baltic network in Figure 2 and its generation, load, and transmission-line data from [35] as a base system for developing our case study. The system has a total of 14 nodes, of which six (without country codes) are dummy nodes used to represent the transmission network and have no load. The dashed and solid lines in Figure 2 are DC and AC links, respectively. We augment this base system by having ten time steps in the CC master problem (\( t \)) for making investments. For each master problem time step, we consider 24 time steps in the CC subproblem (\( \tau \)) to capture the intraday variability of load and renewables. Consequently, the subproblem has 240 time steps in total.

To consider increasing electricity demand, we assume that load values increase by a factor of \( D = 1.01 \) at each master problem time step [37].

In addition, we define 15 operational conditions \( o \) for each subproblem time step. We apply the hierarchical clustering method of [33] on hourly load and wind power data for 2014 to obtain 15 representative days. In short, we concatenate the hourly load and wind power data for each non-dummy node to obtain 365 vectors of length 192 (24 hours \( \times \) 8 non-dummy nodes). These vectors are clustered using agglomerative clustering with Ward’s linkage into the desired number of representative days (15 in our case). We then find the center of each cluster by taking the mean of the vectors in the cluster. Next, we obtain the representative days by finding the nearest vector to the cluster center using mean absolute distance. The hourly load, wind, and solar power data in these 15 representative days are used as the operational conditions for each set of 24 subproblem time steps. This allows us to capture the short-term variability of load and renewables over 15 representative days for each CC master problem time step (\( t \)). We select 15 representative days because we observed that the accuracy of the clustering as measured by mean squared distance from cluster centers does not improve significantly with additional representative days (see Figure 3), while the solution time of the SARO problem steadily increases. For comparison, reference [33] finds 6 representative days appropriate. In fact, [38] show that if a sufficient number of the constraints corresponding to all scenarios are sampled, then
the resulting solution fails to satisfy only a small portion of them.

Since hydropower data such as initial storage levels ($S_{o,t,u}^0$) and inflows ($I_{o,t,u}$) have weekly granularity, for each operating condition, we take the weekly value corresponding to each representative day. However, for generation ($G_{o,t,u}$) and transmission capacities ($F_{o,t,f}$ and $E_{o,t,f}$), the operating conditions are defined by sampling uniform noise from $U(-50\text{ MW}, 50\text{ MW})$ and adding the noise to historical values of these variables from [35]. Likewise, we sample perturbations to conventional generation costs ($C_{o,t,u}^{\text{cg}}$) from $U(-1\text{€/MWh}, 1\text{€/MWh})$. These perturbations represent the short-term variability in generation costs as well as generator and transmission capacities due to maintenance and market conditions, for example. The perturbations are small compared to the historical values of these variables. The weights of the operating conditions ($W_o$) are equal to the weights of the representative days as defined in [33].

Open-cycle gas turbine (OCGT), combined-cycle gas turbine (CCGT), oil, biomass, wind, and solar power can be built at each (non-dummy) node. Each candidate unit has a maximum capacity ($G_{o,t,u}^{\text{inv,max}}$) of 10 GW except for biomass units, which we limit to 1 GW due to limited fuel supply. In addition, neighboring (non-dummy) node pairs can be connected with a candidate DC transmission line with 1 GW of capacity in either direction. The investment costs for OCGT, CCGT, oil, biomass, wind, and solar power are 0.8, 1.0, 0.8, 3.9, 1.6, and 1.8 million €/MW, respectively, and 1000 million € for each transmission line [39]. The discount factor is 1.03, which is typical for this region [40]. We use the factor $P = \frac{1}{1.03}$ to annualize the expansion costs to the same level as the operational costs.

The initial CO$_2$ emission limit $E_0 = 90000$ tonnes is obtained from the CO$_2$ emissions corresponding to the first master problem time step when solving the problem with no investments. This initial emission bound is realistic given that the average daily CO$_2$ emissions of both power and heat production were approximately $E_0 = 140000$ tonnes in this area in 2014 [41]. We assume that the CO$_2$ emissions are required to decrease by approximately 6000 tonnes at every master problem time step to a final emission limit of $E_0 = 35000$ tonnes.

The 2nd level of the problem (1)-(4) chooses the worst-case load for power-system operations at the 3rd level. The budget ($\Delta_w$) for choosing the worst-case load in Eq. (6) is 4 meaning that the model can increase load at a maximum of four nodes. Each increase that the model makes increases load in a node for all operating conditions and subproblem time steps ($\hat{D}_{o,t,u}$) by 5% of average hourly load in that node.

### B. Summary of results

We solve the case study using Algorithm 1 such that, for the CC master problem, we consider MILP and Benders decomposition formulations and, for the CC subproblem, we consider MILP and MIQP formulations. The results in Table I show that all formulations attain the same objective value using the same number of iterations. The majority of the time is spent solving the CC master problems, which Benders decomposition solves nearly 2.5x faster than MILP. For the CC subproblems, MIQP outperforms MILP with a 1.5x speed-up. Consequently, Benders decomposition significantly reduces computational resource usage and, consequently, solution times, at the cost of a more technically complex implementation. The employment of MIQP to solve the subproblems yields smaller improvements in solution times but removes the need for the big-M linearization used in [4], [5], and in many bi-level model instances. This demonstrates contributions C1 and C2.

<table>
<thead>
<tr>
<th>Master problem</th>
<th>Subproblem</th>
<th>MILP</th>
<th>MIQP</th>
<th>MILP</th>
<th>MIQP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obj. func. value (M€)</td>
<td>124.2963</td>
<td>124.2963</td>
<td>124.2963</td>
<td>124.2963</td>
<td></td>
</tr>
<tr>
<td>Solution time (h)</td>
<td>7.08</td>
<td>7.17</td>
<td>15.62</td>
<td>16.19</td>
<td></td>
</tr>
<tr>
<td>Subprob. soln. time (h)</td>
<td>0.45</td>
<td>0.66</td>
<td>0.45</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td>Iterations</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

**Table I**

RESULTS FOR THE DIFFERENT MASTER AND SUBPROBLEM ALGORITHMS USING THE NORDIC AND BALTIC NETWORK

Figure 4 shows the evolution of CO$_2$ emissions to the final desired level during the planning horizon and the corresponding CO$_2$ emission prices ($\beta$). Already at $t = 0$, 1000 MW transmission lines are built from Finland to Norway and Sweden (see Table II) and a total of 1650 MW of wind power in Finland as well as 1200 MW of CCGT units in Latvia and Lithuania as shown by Figure 5. As a consequence, CO$_2$ emissions from $t = 0$ to $t = 4$ are below the limits. To reduce CO$_2$ emissions to meet the final level under increasing load, an additional 100 MW of CCGT and 2000 MW of biomass units in Finland and in the Baltic countries are built during steps $t = 5$ to $t = 9$. The generation investments are similar to those in [21] except that they have less CCGT and more solar power. Additionally, we find that our generation-expansion plan remains similar if we decrease the generation-investment costs by 40%-50%. If wind-power investment costs
are decreased further, then the model prefers to build more wind-power capacity due to its low operational costs. In all cases, transmission-line expansion remains unchanged. Hence, we have tested the validity of our results with respect to the assumed cost estimates and found that the main insights are unaffected.

The generation mixes in Figure 6 show that, compared to a solution with minimal investments and no emission constraint, the transmission and generation investments of the SARO model allow for replacing coal-, oil- and oil-shale-fired generation with less-polluting gas- and biomass-fired generation as well as wind power. In addition, new transmission lines between Finland, Norway, and Sweden enable increasing hydropower and nuclear generation close to their maximum capacity.

For the sake of comparison, we consider the investment decisions from an SP or randomly sampled model, in which the 2nd level uncertainty is modeled by representing the load increase (\( \hat{D}_{o,\tau,n} \)) of non-dummy nodes by a set of randomly sampled values. More precisely, we sample a vector of random values \( \hat{w}_n \) from a uniform distribution and scale the magnitude of the vector to 1 to obtain the load for the SP or randomly sampled model:

\[
\sum_n \hat{w}_n = 1
\]

\[
d_{o,\tau,n} = D^{(\tau)}(\hat{D}_{o,\tau,n} + \hat{w}_n \hat{D}_{o,\tau,n}) \quad \forall o, \tau, n
\]

The scaling in Eq. (53) is selected to represent an average load increase across all nodes. Consequently, the SP or randomly sampled model is given by

\[
\min_{\phi, t} P \sum_t R^{-t} \left[ \sum_{u \in \mathcal{G}^+} C_{t,u}^{x} \hat{x}_{t,u} + \sum_{t, \ell} C_{t,\ell}^{y} \hat{y}_{t,\ell} \right] + \min_{\phi, t} \sum_{o} W_o \sum_{\tau} R^{-t(\tau)} \sum_{u} C_{o,\tau,u}^{g} g_{o,\tau,u}
\]

s.t.

Eqs. (2)–(4)

Eqs. (53)–(54)

The objective function in Eq. (55) is the same as in the SARO model in Eqs. (1)–(4) except that the 2nd level objective function (max) is removed. This is because the 2nd level constraints (5)–(6) are replaced by Eqs. (53)–(54), which allocate the load increase (\( \hat{D}_{o,\tau,n} \)) to non-dummy nodes randomly instead of finding the worst-case load increase. This makes \( d_{o,t,n} \) a parameter in the SP or randomly sampled model, whereas in the SARO model \( d_{o,t,n} \) is a variable. The SP or randomly sampled model has the same constraints (7)–(21) as the SARO model 2nd-level constraints (represented by the feasibility set \( \Xi \)). Furthermore, the operating conditions (scenarios) remain the same.

The SP or randomly sampled model can, in principle, be solved as an MILP by substituting \( x_{t,u} = x_{t,u}^{*} \) and \( y_{t,\ell} = y_{t,\ell}^{*} \) in the SP or randomly sampled model formulation. However, we solve this SP or randomly sampled model using the same CC algorithm as we use for solving our base SARO model except that in Algorithm 1, we set \( d_{o,t,n} = d_{o,t,n,v} = d_{o,t,n}^{*} \). The CC algorithm can potentially speed-up the computational performance of large problem instances.

Figure 7 shows the generation mixes of the SARO and SP (or randomly sampled) models using their investment decisions and the same load. Compared to the SP or randomly sampled model, the SARO model allows for replacing coal-, oil-, gas-, and oil-shale-fired generation with wind power. Compared to the worst-case demand increases selected by the SARO model, the randomly allocated demand increases of the SP or randomly sampled model lead to lower transmission network congestion that leads the SP or randomly sampled model to invest less in wind power and utilize more existing hydro, biomass, and less-polluting gas plants.

![Fig. 4. CO₂ emissions and prices during the planning horizon](image)

### C. Impact of uncertainty budget

The optimal generation and expansion decisions for different uncertainty budgets lead to Finland-Norway and Finland-Sweden transmission lines and gas-fired, biomass, and wind power in all cases, which indicates the robustness of the investment decisions (Table II). Investments in wind power grow in relative terms at higher uncertainty levels. All models are solved using Benders decomposition and MIQP. This demonstrates contribution C3.

<table>
<thead>
<tr>
<th>Uncertainty (A%)</th>
<th>Transmission (GW)</th>
<th>Generation (GW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FL-NO</td>
<td>FL-SE</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>5</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>4</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>5</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>6</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>5</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**TABLE II**

RESULTS FOR THE IMPACT OF UNCERTAINTY BUDGET ON THE EXPANSION PLAN IN THE SARO MODEL

Table III shows the investment plan made by an SP or randomly sampled model in which the load increases (\( \hat{D}_{o,\tau,n} \))
are randomly allocated to the nodes. The transmission line investments are the same as those in the SARO model, but generation investments in biomass are lower without investment in wind power.

<table>
<thead>
<tr>
<th>Uncertainty $D_{o,\tau,n}$ (%)</th>
<th>Transmission (GW)</th>
<th>Generation (GW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FI-NO</td>
<td>FI-SE</td>
</tr>
<tr>
<td>3</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>5</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**TABLE III**

RESULTS FOR THE IMPACT OF LOAD UNCERTAINTY ON THE EXPANSION PLAN IN THE SP OR RANDOMLY SAMPLED MODEL

**D. Cost of robustness**

Next, we demonstrate contribution C4 by evaluating the out-of-sample performance of the investment plan made by the SARO model by computing its expected total costs under different load levels sampled from $d_{o,\tau,n} \sim \tilde{D}_{o,\tau,n} [1 + U(\min(0,L), \max(0,L))], \forall o,\tau,n$, where $L \in [-0.05,0.10]$ is a load change. As we have 15 operating conditions, 240 time steps, and 8 non-dummy nodes, we sample a total of $15 \times 240 \times 8 = 28800$ load change values. Otherwise, we use the same parameter values as in our base model in Section IV-B. As a comparison, we use the investment plan made by an SP or randomly sampled model of Section IV-B in which the load increases of 5% ($\tilde{D}_{o,\tau,n}$) are randomly allocated to the nodes.

Since the models can become infeasible at higher load levels, we relax the emission constraints and assign different...
penalty levels for violating them. This penalty corresponds to the marginal emissions cost $\beta e_t$, which reaches the range 50 €/tonne to 500 €/tonne in our base model as shown by Figure 4. We expect the emission cost to increase as the emission policy is anticipated to get more stringent over time and, hence, consider penalty levels of 100, 1000, and 10,000 €/tonne. Figure 8 indicates that the SARO model is more conservative in that it has higher total costs when load changes are zero or negative. However, for positive load changes, the SARO model can have lower total costs than the SP or randomly sampled model when the penalty for violating the emission constraint is 1000 €/tonne or higher. Moreover, for load changes close to the upper limit, the SP or randomly sampled model becomes infeasible.

**E. Impact of detailed hydro-reservoir modeling**

To further demonstrate our contributions C3 and C4, we remove the hydropower storage variable $s_{o,t,u}$ and constraints (12)-(15) from the problem (1)-(4) to explore the impact of detailed power-system modeling. In effect, we treat hydro-reservoir generation as if it were a fully flexible resource. We find that without the hydropower constraints, there is no new generation investment while 1000 MW transmission lines are built from Finland to Norway and Sweden at $t = 0$ similar to our base model in Section IV-B. Following Section IV-D, we evaluate the investment plan made by the SARO model without the hydropower storage constraints by inserting the storage constraints back and computing the total expected cost under different load changes $L$ and penalties for violating the emission constraints. Figure 9 shows that the investment plan made by the SARO model with hydropower storage constraints has slightly higher total costs when the penalty for violating the emission constraints is 100 €/tonne. However, when either the penalty is 1000 €/tonne or the load change $L$ is higher than 6%, the investment plan made by the SARO model without storage constraints either leads to significantly higher total costs or results in infeasibility as indicated by the truncated blue series in Figure 9. Consequently, it is important to model hydropower at a detailed level to obtain realistic investment decisions that can avoid severe economic consequences and issues with power-system adequacy.

**V. CONCLUSIONS**

Many nations have set specific goals for GHG emission reductions through measures such as increasing the share of renewable energy. Integrating substantial VRES capacities in existing power systems is likely to require significant investments in transmission capacity and flexible generation technologies to guarantee power-system adequacy and security in the short and long terms. Therefore, the first contribution (C1) of this paper is to propose a SARO model for the G&TEP problem with multiple long- and short-term time periods along with detailed power-system operations and an emission-reduction goal. Earlier work has either omitted detailed short-term power-system operations, considered fixed investment scenarios, or not focused on emission reduction. Our second contribution (C2) is to deploy Benders decomposition and MIQP reformulations for improving the solution time of the problem. Earlier work has either used expensive big-M linearizations to obtain an expensive MILP or developed methods to accelerate the CC subproblem that may not be the computational bottleneck in all cases. We apply the model to a Nordic and Baltic power system and make the following conclusions on energy policy to contribute to the state-of-the-art policy analysis of large-scale integration of renewable energy in power systems (C3 and C4):

1) New transmission lines are built to make flexible and environmentally friendly hydropower production available in the entire system. The investment decisions are robust to load uncertainty and changes in generation-investment costs.
2) New wind power units are built to reduce emissions. In addition, CCGT and biomass generation units are built to displace more polluting coal, oil, and oil-shale units and to provide flexibility for offsetting the variability of wind and solar power. Building more wind power is preferred at higher uncertainty levels.

3) The SARO model invests more in biomass and wind power than the SP or randomly sampled model does.

4) The investment plan found by the SARO model outperforms that of an SP or randomly sampled model at higher load levels but is more expensive at lower load levels.

5) Omitting hydro-reservoir constraints in modeling leads to significantly lower generation investment, which results in higher expected costs and infeasibility at higher load levels.

Building on our improved computational methods, future work could explore longer-term investment plans with various scenarios on the electrification of transportation as well as deployment of emerging technologies such as storage other than hydropower. Moreover, the model could be extended to cover larger power systems such as all of Europe to find a more globally optimal investment plan that takes into account the pool of resources and spatio-temporal correlations of VRES generation in a larger geographical area. Our model assumes a central planner, while future work could take game-theoretic approaches with multiple independent market participants. The hydropower model could be further improved to consider the time value of water and constraints related to river systems. Also, future research can develop more realistic models for additional sources of uncertainty such as long-term uncertainties in fuel costs, transmission and generation outages, and climate conditions affecting renewable-energy availability that could lead to more robust investment plans for renewable-rich systems. In fact, our framework can be readily extended with additional long- and short-term uncertainties at the 2nd and 3rd levels of the model, respectively. Finally, the large-scale LP in the Benders subproblem remains a bottleneck, which means that further decomposition could lead to significant improvements in solution times.

REFERENCES


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