

Achieving emission reduction goals: Long-term power system expansion under short-term operational uncertainty

Authors here

Abstract—Recent work employs two-stage robust optimization to deal with uncertain demand and generation parameters in the generation and transmission expansion planning problem. We build on this work by considering multi-year investment horizon with an objective of reducing greenhouse gas emissions. In addition, we consider multiple hours in power system operations to capture the flexibility requirements for utilizing variable renewable energy sources such as wind and solar power. To improve the solution time of the existing exact methods for this problem, we employ Benders decomposition and solve a mixed-integer quadratic problem to avoid expensive big-M-linearizations. The results for a realistic case study for the Nordic and Baltic countries show the effectiveness of our solution method. Also, the results indicate that investments in new transmission lines, wind power and flexible generation capacity are required for reducing greenhouse gas emissions in this area.

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

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, for example [1]. To this end, there are nation-level 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 hydro power and biomass, investments in non-dispatchable, variable RES (VRES) such as wind and solar power are required. However, integrating large investments in VRES to existing power systems is likely to require significant investments in transmission capacity as well as to flexible generation technologies (e.g. combined cycle gas turbines, CCGT) and storage to guarantee the power system adequacy and security [3].

Consequently, in this paper, we consider the Generation and Transmission Expansion Planning (G&TEP) problem with the objective of reducing GHG emissions under uncertain demand and VRES generation, for example. More specifically, we employ a tri-level model representing two stages 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 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. This combination of RO and stochastic programming in two stages is called stochastic adaptive robust optimization (SARO) [4]. This framework allows us to study what transmission line, VRES, and other generation investments are required to meet long-term GHG emission reduction goals while meeting short-term operational constraints on demand, transmission, generator ramping and availability with random and worst-case realizations of the related parameters. We apply the framework to a realistic case study covering the Nordic and Baltic countries.

Similar tri-level framework is employed for the G&TEP problem in [5], [6], [4] but without the multi-year and multi-hour time dimensions and a goal for GHG emission reduction. [7], [8] consider multiple years but they do not focus on GHG emission reduction, do not model storage or hydro power, and use different solution techniques. Also, the G&TEP problem has been studied extensively in single- ([9], [10], [11], [12]) and bi-level settings ([13], [14], [15]) but these do not employ RO for uncertainty modeling.

Likewise, approaches for GHG emission reduction in the energy system have been studied extensively. [16], [17], [18], and [19] explore the long-term plan toward a fully renewable power system in Germany, Australia, California, and Japan respectively. They all find that significant amount of vRES generation needs to be complemented with dispatchable RES generation as well as storage technologies. However, their methodologies are limited in that they consider fixed cases for generation and transmission expansion and omit details such as transmission network, certain generation types, or ramping in short-term power system operations. In fact, [20] solve for an expansion plan with constraints on GHG emissions and the share of RES generation and show that ignoring operational constraints leads to large errors in estimating GHG emissions.

Typically, the G&TEP problem is solved from the perspective of a central planner such as the transmissions system operator (TSO). Although transmission investments are often made by such a central planner, the generation investments are usually made by independent market participants [4]. However, the central planner may use incentive policies to encourage investment into certain generation units [21], [22]. Nevertheless, [23], [24], [25] consider multiple companies investing in generation but this leads to problems with multiple equilibria which require custom solution algorithms, possibly with computationally expensive linearization schemes and no optimality guarantees.

Even with the simplifying assumption of a central planner, the tri-level 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) that can be reformulated as a computationally expensive MILP using big-M-based linearization. To this end, [26] develop an approximate block coordinate descent method to avoid the expensive linearization of the subproblem and thereby accelerate its solution. Other inexact solution methods involve metaheuristics such as genetic algorithms [27] and particle swarm optimization [28]. However, in this paper, we note that the subproblem is an MIQP, which can be solved faster than the linearized MILP using modern solvers such as Gurobi. 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 ([29]) 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.

Given this context, the contributions of this paper are:

- 1) To consider multi-year and multi-hour time scales in a SARO problem for G&TEP.
- 2) To consider detailed power system operations including hydro power and a constraint for emissions in a realistic case study for Nordic and Baltic countries.
- 3) 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.

The remaining of this paper is organized as follows. Section II presents the mathematical formulation of our SARO problem. Section III presents a realistic case study and its results. Finally, Section IV provides conclusions.

II. PROBLEM DESCRIPTION

At the upper level of our SARO problem, we consider a central planner that makes generation and transmission expansion decisions in a long-term horizon consisting of time steps t that can be interpreted as years, for example. While making the expansion plan, the central planner considers the lower level of the SARO problem in which a market operator minimizes power system operation costs in each upper-level time step t under worst case demand and multiple operating conditions o that represent uncertainty in generation cost parameters and VREs generation, for example. In order to capture the variability in demand and VRE generation, we model power system operations within each upper-level time step t using a number of lower-level time steps τ that can be interpreted as hours, for example. In addition to attaining minimum cost operations, the central planner is required to

consider an upper bound for emissions in each upper-level time step.

A combination of robust optimization and stochastic programming is used for modeling uncertainty when making the expansion plan. Following [4], we use robust optimization to identify worst case realization for long-term uncertainties such as demand. On the other hand, stochastic programming is used to model short-term uncertainties such as VREs generation.

A. Notation

Indices

n	node
u	generation unit
ℓ	transmission line
o	operating condition
t	time step in the master problem
τ	time step in the subproblem
ν	iteration in the column-and-constraint algorithm

Sets

Ψ^G	existing generation units
Ψ^L	existing transmission lines
$\Psi^{L,AC}$	existing alternating current (AC) transmission lines
$\Psi^{G,H}$	existing hydro units
Ψ^{G+}	candidate generation units
Ψ^{L+}	candidate transmission lines
$\Phi^{L1/L2/L3}$	1st/2nd/3rd level decision variables
Ω^M	master problem decision variables
Ω^S	subproblem decision variables
Ω	uncertainty set
Ξ	feasibility set
$r(\ell)/s(\ell)$	receiving/sending-end node of line ℓ
T^0	first subproblem time step within each master problem time step
T^{-1}	last subproblem time step within each master problem time step
T^{ramp}	subproblem time steps in which the ramp constraints are considered

Parameters

P	scaling factor to make investment and operation costs comparable
W_o	weight of operating condition o
D	demand growth factor
$\tilde{D}_{o,\tau,n}$	nominal demand at node n in condition o in period τ (MWh)
$\hat{D}_{o,\tau,n}$	demand increase at node n in condition o in period τ (MWh)
E_t	CO ₂ emission target in period t (tonne)
R	discount factor
$C_{t,u}^x$	investment cost per 1 MW of candidate unit u in period t (€)

$C_{t,\ell}^y$	investment cost of building candidate transmission line ℓ in period t (€)
C_u^g	generation cost of unit u (€/MWh)
$A_{o,\tau,u}$	availability of unit u in condition o in period τ (%)
$G_u^{inv,max}$	maximum invested capacity in candidate unit u (MW)
$G_{o,\tau,u}^{max}$	maximum generation of unit u in condition o in period τ (MWh)
$G_{o,\tau,u}^{ramp,max}$	maximum ramp up of unit u in condition o in period τ (MWh)
$G_{o,\tau,u}^{ramp,min}$	maximum ramp down of unit u in condition o in period τ (MWh)
$G_u^{emission}$	CO ₂ emission rate of unit u (tonne/MWh)
$S_{o,\tau,u}^0$	initial storage level of hydro unit u in condition o in period τ (MWh)
$S_{o,\tau,u}^{max}$	maximum final storage level of hydro unit u in condition o in period τ (MWh)
$S_{o,\tau,u}^{min}$	minimum final storage level of hydro unit u in condition o in period τ (MWh)
$I_{o,\tau,u}$	inflow to hydro unit u in condition o in period τ (MWh)
$F_{o,\tau,\ell}^{max}$	maximum flow on line ℓ in condition o in period τ (MWh)
$F_{o,\tau,\ell}^{min}$	minimum flow on line ℓ in condition o in period τ (MWh)
B_ℓ	susceptance of line ℓ (1/Ω)
Λ^w	demand uncertainty budget
$\Lambda^{min/max}$	minimum/maximum price in the exchange (€/MWh)

Binary variables

$\hat{y}_{t,\ell}$	equals 1 if the investment in candidate transmission line ℓ is made in period t
$y_{t,\ell}$	equals 1 if candidate transmission line ℓ is available in period t
w_n	equals 1 if demand is increased from the nominal level at node n

Continuous variables

$\hat{x}_{t,u}$	new capacity of candidate generation unit u built in period t (MW)
$x_{t,u}$	total built capacity of candidate generation unit u in period t (MW)
$d_{o,\tau,n}$	uncertain demand at node n in condition o in period τ (MWh)
$z_{o,\tau,n}$	auxiliary variables for linearizing $\lambda_{o,\tau,n}d_{\tau,n}$ (€)
$\lambda_{o,\tau,n}$	price in condition o at node n in period τ (€/MWh)
$\tilde{\lambda}_{o,\tau,n}$	auxiliary variables for linearizing $\lambda_{o,\tau,n}d_{\tau,n}$ (€)
$f_{o,\tau,\ell}$	transmission flow in line ℓ in condition o in period τ (MWh)

$\delta_{o,\tau,n}$	voltage angle at node n in condition o in period τ (rad)
$g_{o,\tau,u}$	generation at unit u in condition o in period τ (MWh)
$s_{o,\tau,u}$	storage at hydro unit u in condition o in period τ (MWh)
$\bar{\beta}_{o,\tau,u}$	dual variable for maximum generation of unit u in condition o in period τ (€/MWh)
$\bar{\beta}_{o,\tau,u}^{ramp}$	dual variable for maximum ramp up of unit u in condition o in period τ (€/MWh)
$\underline{\beta}_{o,\tau,u}$	dual variable for minimum generation of unit u in condition o in period τ (€/MWh)
$\underline{\beta}_{o,\tau,u}^{ramp}$	dual variable for maximum ramp down of unit u in condition o in period τ (€/MWh)
$\beta_t^{emission}$	dual variable for maximum CO ₂ emission in period t (€/MWh)
$\phi_{o,\tau,u}^0$	dual variable for initial storage level of hydro unit u in condition o in period τ (€/MWh)
$\underline{\phi}_{o,\tau,u}$	dual variable for minimum storage of hydro unit u in condition o in period τ (€/MWh)
$\phi_{o,\tau,u}$	dual variable for storage level of hydro unit u in condition o in period τ (€/MWh)
$\bar{\phi}_{o,\tau,u}^{-1}$	dual variable for maximum final storage level of hydro unit u in condition o in period τ (€/MWh)
$\underline{\phi}_{o,\tau,u}^{-1}$	dual variable for minimum final storage level of hydro unit u in condition o in period τ (€/MWh)
$\mu_{o,\tau,\ell}$	dual variable for flow in AC line ℓ in condition o in period τ (€/MWh)
$\bar{\mu}_{o,\tau,\ell}$	dual variable for maximum flow in line ℓ in condition o in period τ (€/MWh)
$\underline{\mu}_{o,\tau,\ell}$	dual variable for minimum flow in line ℓ in condition o in period τ (€/rad)
$\bar{\mu}_{o,\tau,n}^{va}$	dual variable for maximum voltage angle at node n in condition o in period τ (€/rad)
$\underline{\mu}_{o,\tau,n}^{va}$	dual variable for minimum voltage angle at node n in condition o in period τ (€/rad)
$\mu_{o,\tau}^{ref}$	dual variable for reference node voltage angle in condition o in period τ (€/MWh)
θ	auxiliary variable for the column-and-constraint master problem objective function (€)

B. Stochastic adaptive robust optimization problem

We use Ω and Ξ to denote the uncertainty and feasibility sets, respectively. The stochastic adaptive robust optimization problem is

$$\min_{\Phi^{L1}} P \sum_t R^{-t} \left[\sum_{u \in \Psi^{G+}} C_{t,u}^x \hat{x}_{t,u} + \sum_{\ell \in \Psi^{L+}} C_{t,\ell}^y \hat{y}_{t,\ell} \right] + \max_{\Phi^{L2} \in \Omega} \min_{\Phi^{L3} \in \Xi} \sum_o W_o \sum_\tau R^{-t(\tau)} \sum_u C_u^g g_{o,\tau,u} \quad (1)$$

subject to

$$x_{t,u} = \sum_{t'=1}^t \hat{x}_{t',u} \quad \forall t, u \in \Psi^{G+} \quad (2)$$

$$y_{t,\ell} = \sum_{t'=1}^t \hat{y}_{t',\ell} \quad \forall t, \ell \in \Psi^{L+} \quad (3)$$

$$x_{t,u} \leq G_u^{inv,max} \quad \forall t, u \in \Psi^{G+} \quad (4)$$

where $\Phi^{L1} = \{\hat{x}_{t,u}, x_{t,u}, \forall u \in \Psi^{G+}; \hat{y}_{t,\ell}, y_{t,\ell}, \forall \ell \in \Psi^{L+}\}, \forall t$,
 $\Phi^{L2} = \{d_{o,\tau,n}, \forall o, \tau; w_n\}, \forall n$, and
 $\Phi^{L3} = \{g_{o,\tau,u}, \forall u; s_{o,\tau,u}, \forall u \in \Psi^{G,H}; f_{o,\tau,\ell}, \forall \ell; \delta_{o,\tau,n}, \forall n\}, \forall o, \tau$.

In the objective function (1), the first minimization problem represents the annualized generation and transmission expansion costs and the max-min problem represents minimal operation costs under the worst case realization of demand and a set of operating conditions for other uncertain parameters. The constraints (2) and (3) define the available new generation capacity and transmission lines at the upper-level time step t as the sum of investments up to t . The constraint (4) imposes upper bounds for the capacities of the new generation units.

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

$$\{d_{o,\tau,n} = D^{-t(\tau)}(\tilde{D}_{o,\tau,n} + w_n \hat{D}_{o,\tau,n}) \quad \forall o, \tau, n \quad (5)$$

$$\sum_n w_n \leq \Lambda^w\}. \quad (6)$$

Eq. (5) defines that demand is equal to the sum of nominal demand ($\tilde{D}_{o,\tau,n}$) and a possible demand increase ($\hat{D}_{o,\tau,n}$) multiplied by demand growth factor (D) that accrues at each upper-level time step. The demand increase is selected using binary variables w_n to cause the maximum operation costs. Eq. (6) sets an uncertainty budget to how many demand increases the model can do.

Given the optimal values $x_{t,u}^*, \forall t, u \in \Psi^{G+}$, $y_{t,\ell}^*, \forall t, \ell \in \Psi^{L+}$, and $d_{o,\tau,n}^*, \forall o, \tau, n$, the feasibility set $\Xi(g_{o,\tau,u}, s_{o,\tau,u}, f_{o,\tau,\ell}, \delta_{o,\tau,n})$ is

$$\left\{ \begin{aligned} & \sum_{u|n(u)=n} g_{o,\tau,u} - \sum_{\ell|s(\ell)=n} f_{o,\tau,\ell} + \\ & \sum_{\ell|r(\ell)=n} f_{o,\tau,\ell} = d_{o,\tau,n}^* \quad \forall o, \tau, n \end{aligned} \right. \quad (7)$$

$$0 \leq g_{o,\tau,u} \leq A_{o,\tau,u} G_{o,\tau,u}^{max} \quad \forall o, \tau, u \in \Psi_n^G \quad (8)$$

$$0 \leq g_{o,\tau,u} \leq A_{o,\tau,u} x_{t(\tau),u}^* \quad \forall o, \tau, u \in \Psi_n^{G+} \quad (9)$$

$$G_{o,\tau,u}^{ramp,min} \leq g_{o,\tau+1,u} - g_{o,\tau,u} \quad \forall o, \tau \in T^{ramp}, u \quad (10)$$

$$g_{o,\tau+1,u} - g_{o,\tau,u} \leq G_{o,\tau,u}^{ramp,max} \quad \forall o, \tau \in T^{ramp}, u \quad (11)$$

$$s_{o,\tau,u} \geq 0 \quad \forall o, \tau, u \in \Psi^{G,H} \quad (12)$$

$$s_{o,\tau,u} = s_{o,\tau,u}^0 \quad \forall o, \tau \in T^0, u \in \Psi^{G,H} \quad (13)$$

$$s_{o,\tau+1,u} = s_{o,\tau,u} - g_{o,\tau,u} + I_{o,\tau,u} \quad \forall o, \tau \in T^{ramp}, u \in \Psi^{G,H} \quad (14)$$

$$S_{o,\tau,u}^{min} \leq s_{o,\tau,u} \leq S_{o,\tau,u}^{max} \quad \forall o, \tau \in T^{-1}, u \in \Psi^{G,H} \quad (15)$$

$$f_{o,\tau,\ell} = B_\ell(\delta_{o,\tau,s(\ell)} - \delta_{o,\tau,r(\ell)}) \quad \forall o, \tau, \ell \in \Psi^L \quad (16)$$

$$F_{o,\tau,\ell}^{min} \leq f_{o,\tau,\ell} \leq F_{o,\tau,\ell}^{max} \quad \forall o, \tau, \ell \in \Psi^L \quad (17)$$

$$F_{o,\tau,\ell}^{min} y_{t(\tau),\ell}^* \leq f_{o,\tau,\ell} \leq F_{o,\tau,\ell}^{max} y_{t(\tau),\ell}^* \quad \forall o, \tau, \ell \in \Psi^{L+} \quad (18)$$

$$-\pi \leq \delta_{o,\tau,n} \leq \pi \quad \forall o, \tau, n \quad (19)$$

$$\delta_{o,\tau,0} = 0 \quad \forall o, \tau \quad (20)$$

$$\sum_o \sum_{\tau \in t} \sum_u W_o G_{o,\tau,u}^{emission} g_{o,\tau,u} \leq E_t \quad \forall t \quad (21)$$

where the notation $n(u)$ indicates the node in which unit u is located and $t(\tau)$ the upper-level time step t that the lower-level time step τ is assigned to. Also, the notation $\tau \in t$ indicates lower-level time steps τ within an upper-level time step t . The definition of the two different time scales and the related sets are shown in Figure 1.

Eqs. (7)-(20) represent the power system operations. Eq. (7) requires that demand equals generation and exchange at each node. Eqs. (8) and (9) impose that generation is non-negative but less than or equal to a quantity given by the product of availability ($A_{o,\tau,u}$) and maximum capacity of an existing unit ($G_{o,\tau,u}^{max}$) or the built capacity of a candidate unit $x_{t(\tau),u}^*$, respectively. Moreover, generation is limited by ramping constraints (10) and (11).

Following [30], we assume that each hydro power unit has one reservoir that can act as a storage. Eq. (12) imposes that storages are always non-negative. Eq. (13) sets the initial storage level at the first lower-level time step τ within each upper-level time step t . Eq. (14) requires that the storage level at the following time step τ is given by the difference of hydro power generation and inflows $I_{o,\tau,u}$. Finally, Eq. (15) requires that the storage level at the last lower-level time step τ of each upper-level time step t is within desired levels $S_{o,\tau,u}^{min}$ and $S_{o,\tau,u}^{max}$. Otherwise, the storage could be depleted, which would cause problems later on.

The transmission network is represented by active 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 (19) and (20), respectively.

Finally, Eq. (21) determines the upper bound for CO₂ emission at each upper-level time step t .

Finally, we assume that all candidate transmission lines are direct current (DC) lines. This assumption reduces solution times because alternating current (AC) candidate lines would lead to constraints with a product of a binary and a continuous variable, which we would need to linearize.

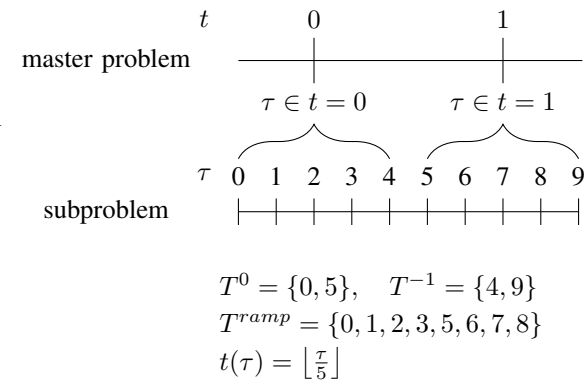


Fig. 1. T^0 , T^{ramp} , T^{-1} , $t(\tau)$, and $\tau \in t$ in an example problem with five subproblem timesteps within each of the two master problem time steps

C. Overview of the solution algorithm

The problem (1)-(4) is solved using 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 (Eqs. (22)-(39)) and CC subproblem (Eqs. (40)-(45)), respectively. The alternation terminates when the total costs computed from the two problems match. The solution algorithm is described in detail in Algorithm 1.

Input: Transmission and generation parameters, CO₂ emission targets

Output: Transmission and generation expansion plan
 $\epsilon \leftarrow 10^{-6}$

$LB \leftarrow -\infty$

$UB \leftarrow \infty$

$\nu \leftarrow 0$

$d_{o,\tau,n,\nu} \leftarrow \tilde{D}_{o,\tau,n} \quad \forall o, \tau, n$

while $(UB - LB)/UB \leq \epsilon$ **do**

 // Solve the CC master problem

 Obtain $x_{t,u}^*, \hat{x}_{t,u}^*, \forall t, u \in \Psi^{G+}; y_{t,\ell}^*, \hat{y}_{t,\ell}^*, \forall t, \ell \in \Psi^{L+}$ by solving CC master problem in Eqs. (22)-(39) using $d_{o,\tau,n,\nu}, \forall o, \tau, n, \nu' \leq \nu$. LB is updated to the objective value of the master problem.

 // Solve the CC subproblem

 Obtain $w_n \forall n$ by solving CC subproblem in Eqs. (40)-(45) using the current

$x_{t,u}^*, \forall t, u \in \Psi^{G+}; y_{t,\ell}^*, \forall t, \ell \in \Psi^{L+}$. UB is updated to the objective value of the subproblem + $P \sum_t R^{-t} \left(\sum_{u \in \Psi^{G+}} C_{t,u}^x \hat{x}_{t,u}^* + \sum_{\ell \in \Psi^{L+}} C_{t,\ell}^y \hat{y}_{t,\ell}^* \right)$

$\nu \leftarrow \nu + 1$

$d_{o,\tau,n,\nu} \leftarrow \tilde{D}_{o,\tau,n} + w_n \hat{D}_{o,\tau,n} \quad \forall o, \tau, n$

end

Algorithm 1: Algorithm for solving the problem (1)-(4)

D. CC master problem

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

$$\min_{\Phi^{L1}, \Omega^M, \theta} P \sum_t R^{-t} \left[\sum_{u \in \Psi^{G+}} C_{t,u}^x \hat{x}_{t,u}^* + \sum_{\ell \in \Psi^{L+}} C_{t,\ell}^y \hat{y}_{t,\ell}^* \right] + \theta \quad (22)$$

subject to

$$\text{Eqs. (2) - (4)} \quad (23)$$

$$\theta \geq \sum_o W_o \sum_\tau R^{-t(\tau)} \sum_u C_u^g g_{o,\tau,u,\nu'} \quad \forall \nu' \leq \nu \quad (24)$$

$$\sum_{u|n(u)=n} g_{o,\tau,u,\nu'} - \sum_{\ell|s(\ell)=n} f_{o,\tau,\ell,\nu'} +$$

$$\sum_{\ell|r(\ell)=n} f_{o,\tau,\ell,\nu'} = d_{\tau,n,\nu'}^* \quad \forall o, \tau, n, \nu' \leq \nu \quad (25)$$

$$0 \leq g_{o,\tau,u,\nu'} \leq A_{o,\tau,u} G_{o,\tau,u}^{max} \quad \forall o, \tau, u \in \Psi_n^G, \nu' \leq \nu \quad (26)$$

$$0 \leq g_{o,\tau,u,\nu'} \leq A_{o,\tau,u} x_{t(\tau),u} \quad \forall o, \tau, u \in \Psi_n^{G+}, \nu' \leq \nu \quad (27)$$

$$G_{o,\tau,u}^{ramp,min} \leq g_{o,\tau+1,u,\nu'} - g_{o,\tau,u,\nu'} \quad \forall o, \tau \in T^{ramp}, u, \nu' \leq \nu \quad (28)$$

$$g_{o,\tau+1,u,\nu'} - g_{o,\tau,u,\nu'} \leq G_{o,\tau,u}^{ramp,max} \quad \forall o, \tau \in T^{ramp}, u, \nu' \leq \nu \quad (29)$$

$$\sum_o \sum_{\tau \in t} \sum_u W_o G_{o,\tau,u}^{emission} g_{o,\tau,u,\nu'} \leq E_t \quad \forall t, \nu' \leq \nu \quad (30)$$

$$s_{o,\tau,u,\nu'} \geq 0 \quad \forall o, \tau, u \in \Psi^{G,H}, \nu' \leq \nu \quad (31)$$

$$s_{o,\tau,u,\nu'} = S_{o,\tau,u}^0 \quad \forall o, \tau \in T^0, u \in \Psi^{G,H}, \nu' \leq \nu \quad (32)$$

$$s_{o,\tau+1,u,\nu'} = s_{o,\tau,u,\nu'} - g_{o,\tau,u,\nu'} + I_{o,\tau,u} \quad \forall o, \tau \in T^{ramp}, u \in \Psi^{G,H}, \nu' \leq \nu \quad (33)$$

$$S_{o,\tau,u}^{min} \leq s_{o,\tau,u,\nu'} \leq S_{o,\tau,u}^{max} \quad \forall o, \tau \in T^{-1}, u \in \Psi^{G,H}, \nu' \leq \nu \quad (34)$$

$$f_{o,\tau,\ell,\nu'} = B_\ell (\delta_{o,\tau,s(\ell),\nu'} - \delta_{o,\tau,r(\ell),\nu'}) \quad \forall o, \tau, \ell \in \Psi^L, \nu' \leq \nu \quad (35)$$

$$F_{o,\tau,\ell}^{min} \leq f_{o,\tau,\ell,\nu'} \leq F_{o,\tau,\ell}^{max} \quad \forall o, \tau, \ell \in \Psi^L, \nu' \leq \nu \quad (36)$$

$$F_{o,\tau,\ell}^{min} y_{t(\tau),\ell} \leq f_{o,\tau,\ell,\nu'} \leq F_{o,\tau,\ell}^{max} y_{t(\tau),\ell} \quad \forall o, \tau, \ell \in \Psi^{L+}, \nu' \leq \nu \quad (37)$$

$$-\pi \leq \delta_{o,\tau,n,\nu'} \leq \pi \quad \forall o, \tau, n, \nu' \leq \nu \quad (38)$$

$$\delta_{o,\tau,0,\nu'} = 0 \quad \forall o, \tau, \nu' \leq \nu \quad (39)$$

E. CC subproblem

For the subproblem, we set

$$\begin{aligned} \Omega^S = & \{\bar{\beta}_{o,\tau,u}, \underline{\beta}_{o,\tau,u}, \bar{\beta}_{o,\tau,u}^{ramp}, \underline{\beta}_{o,\tau,u}^{ramp}\}, \forall o, \tau, u \cup \\ & \beta_t^{emission}, \forall t \cup \\ & \{\phi_{o,\tau,u}^0, \forall \tau \in T^0; \phi_{o,\tau,u}, \forall \tau \in T^{ramp}; \\ & \bar{\phi}_{o,\tau,u}^{-1}, \underline{\phi}_{o,\tau,u}^{-1} \quad \forall \tau \in T^{-1}; \underline{\phi}_{o,\tau,u} \quad \forall \tau\}, \forall o, u \in \Psi^{G,H} \cup \\ & \{\mu_{o,\tau,\ell}, \bar{\mu}_{o,\tau,\ell}, \underline{\mu}_{o,\tau,\ell}\} \forall o, \tau, \ell \cup \\ & \{\lambda_{o,\tau,n}, \bar{\mu}_{o,\tau,n}^{va}, \underline{\mu}_{o,\tau,n}^{va}\}, \forall o, \tau, n \cup \\ & \mu_{o,\tau}^{ref}, \forall o, \tau. \end{aligned}$$

With $x_{t,u}^*, \forall t, u \in \Psi^{G+}$ and $y_{t,\ell}^*, \forall t, \ell \in \Psi^{L+}$ as input data obtained from the previous solution of the master problem, the subproblem is

$$\begin{aligned} \text{maximize}_{\Phi^{L2}, \Omega^S} & \sum_o \left(\sum_\tau \left[\sum_n \lambda_{o,\tau,n} d_{o,\tau,n} - \right. \right. \\ & \sum_{u \in \Psi^G} \bar{\beta}_{o,\tau,u} A_{o,\tau,u} G_{o,\tau,u}^{max} - \\ & \sum_{u \in \Psi^{G+}} \bar{\beta}_{o,\tau,u} A_{o,\tau,u} x_{t(\tau),u}^* - \\ & \sum_{\ell \in \Psi^L} \left(\bar{\mu}_{o,\tau,\ell} F_{o,\tau,\ell}^{max} - \underline{\mu}_{o,\tau,\ell} F_{o,\tau,\ell}^{min} \right) - \\ & \sum_{\ell \in \Psi^{L+}} \left(\bar{\mu}_{o,\tau,\ell} F_{o,\tau,\ell}^{max} - \underline{\mu}_{o,\tau,\ell} F_{o,\tau,\ell}^{min} \right) y_{t(\tau),\ell}^* - \\ & \left. \left. \sum_n \pi (\bar{\mu}_{o,\tau,n}^{va} + \underline{\mu}_{o,\tau,n}^{va}) \right] \right) + \end{aligned}$$

$$\begin{aligned}
& \sum_{u \in \Psi^{G,H}} \left[\sum_{\tau \in T^0} \phi_{o,\tau,u}^0 S_{o,\tau,u}^0 + \right. \\
& \sum_{\tau \in T^{ramp}} \phi_{o,\tau,u} I_{o,\tau,u} + \\
& \left. \sum_{\tau \in T^{-1}} \left(\phi_{o,\tau,u}^{-1} S_{o,\tau,u}^{min} - \bar{\phi}_{o,\tau,u}^{-1} S_{o,\tau,u}^{max} \right) \right] + \\
& \sum_{\tau \in T^{ramp}} \sum_u \left(\beta_{o,\tau,u}^{ramp} G_{o,\tau,u}^{ramp,min} - \bar{\beta}_{o,\tau,u}^{ramp} G_{o,\tau,u}^{ramp,max} \right) \\
& \sum_t \beta_t^{emission} E_t
\end{aligned} \quad (40)$$

subject to

$$\begin{aligned}
& \lambda_{o,\tau,n(u)} - \bar{\beta}_{o,\tau,u} + \beta_{o,\tau,u} + \mathbb{1}_{\tau \in T^{ramp} \wedge u \in \Psi^{G,H}} \phi_{o,t,u} - \\
& \mathbb{1}_{\tau \notin T^0} \bar{\beta}_{o,\tau-1,u}^{ramp} + \mathbb{1}_{\tau \notin T^{-1}} \bar{\beta}_{o,\tau,u}^{ramp} + \mathbb{1}_{\tau \notin T^0} \beta_{o,\tau-1,u}^{ramp} - \\
& \mathbb{1}_{\tau \notin T^{-1}} \beta_{o,\tau,u}^{ramp} - W_o G_u^{emission} \beta_{t(\tau)}^{emission} = R^{-t(\tau)} C_u^g W_o \quad \forall o, \tau, u
\end{aligned} \quad (41)$$

$$\begin{aligned}
& \mathbb{1}_{\tau \in T^0} \phi_{o,\tau,u}^0 + \beta_{o,\tau,u}^s - \mathbb{1}_{\tau \notin T^{-1}} \phi_{o,\tau,u} + \mathbb{1}_{\tau \notin T^0} \phi_{o,\tau-1,u} + \\
& \mathbb{1}_{\tau \in T^{-1}} (\phi_{o,\tau,u} - \bar{\phi}_{o,\tau,u}) = 0 \quad \forall o, \tau, u \in \Psi^{G,H}
\end{aligned} \quad (42)$$

$$\begin{aligned}
& -\lambda_{o,\tau,s(\ell)} + \lambda_{o,\tau,r(\ell)} + \mathbb{1}_{\ell \in \Psi^{L,AC}} \mu_{o,\tau,\ell} - \\
& \bar{\mu}_{o,\tau,\ell} + \underline{\mu}_{o,\tau,\ell} = 0 \quad \forall o, \tau, \ell
\end{aligned} \quad (43)$$

$$\begin{aligned}
& - \sum_{\ell \in \Psi^{L,AC} | s(\ell)=n} B_\ell \mu_{o,\tau,\ell} + \sum_{\ell \in \Psi^{L,AC} | r(\ell)=n} B_\ell \mu_{o,\tau,\ell} - \\
& \bar{\mu}_{o,\tau,n}^{va} + \underline{\mu}_{o,\tau,n}^{va} + \mathbb{1}_{n=0} \mu_{o,\tau}^{ref} = 0 \quad \forall o, \tau, n
\end{aligned} \quad (44)$$

$$\text{Eqs. (5) - (6)}, \quad (45)$$

where $\mathbb{1}_{cond}$ equals 1 if $cond$ is true and otherwise 0.

The subproblem can be solved directly as a MIQP using solvers such as Gurobi. Alternatively, the subproblem can be re-formulated as an MILP by linearizing the product of a continuous and a binary variable in $\lambda_{o,\tau,n} d_{o,\tau,n} = \lambda_{o,\tau,n} D^{-t(\tau)} (\bar{D}_{o,\tau,n} + w_n \hat{D}_{o,\tau,n})$ in the objective function (40) exactly with $\lambda_{o,\tau,n} d_{o,\tau,n} = D^{-t(\tau)} (z_{o,\tau,n} \bar{D}_{o,\tau,n} + \lambda_{o,\tau,n} \hat{D}_{o,\tau,n})$ and by adding the following constraints to the subproblem

$$z_{o,\tau,n} = \lambda_{o,\tau,n} - \tilde{\lambda}_{o,\tau,n} \quad \forall o, \tau, n \quad (46)$$

$$\Lambda^{min} w_n \leq z_{o,\tau,n} \leq \Lambda^{max} w_n \quad \forall o, \tau, n \quad (47)$$

$$\Lambda^{min} (1 - w_n) \leq \tilde{\lambda}_{o,\tau,n} \leq \Lambda^{max} (1 - w_n) \quad \forall o, \tau, n, \quad (48)$$

where parameters Λ^{min} and Λ^{max} can be set to exchange-specific values such as -500 €/MWh and 3000 €/MWh, respectively.

III. CASE STUDY: MODIFIED NORDIC AND BALTIC NETWORK

We study what investments are required to decrease the initial CO₂ emissions of the Nordic and Baltic electricity system to a target level under uncertain generation and transmission parameters and worst-case realization of demand. More specifically, we use the Nordic and Baltic network and its generation, load, and transmission line data from [31] as a base.

We augment this base system by having 10 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 (τ). 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 [32].

In addition, we define 3 operation conditions o for each subproblem time step. We apply the hierarchical clustering method of [33] on hourly load and wind power data of 2014 to obtain 3 representative days. The hourly load, wind, and solar power data on these 3 representative days are used as the operating conditions for each set of 24 subproblem time steps. This allows us to capture the short-term variability of load and renewables. Hydro power data such as initial storage levels ($S_{o,\tau,u}^0$) and inflows ($I_{o,\tau,u}$) have weekly granularity so, for each operating condition, we take the weekly value corresponding to each representative day. However, for generation ($G_{o,\tau,u}^{max}$) and transmission capacities ($F_{o,\tau,\ell}^{max}$ and $F_{o,\tau,\ell}^{min}$), the operation conditions are defined by sampling uniform noise from $U(-50 \text{ MW}, 50 \text{ MW})$. The weights of the operation conditions (W_o) are equal to the weights of the representative days as defined in [33].

Gas, CCGT, oil, biomass, wind and solar power can be built at each (non-dummy) node. Each candidate unit has a maximum capacity ($G_u^{inv,max}$) of 10000 MW except for biomass units which we limit to 1000 MW due to limited fuel supply. In addition, neighboring (non-dummy) node pairs can be connected with a candidate DC transmission line with 1000 MW of capacity to both directions. The investment cost parameters are shown in Table I.

The initial CO₂ emission bound $E_0 = 90000$ tonne is obtained from the CO₂ 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 CO₂ emissions of both power and heat production were approximately $E_0 = 140000$ tonne in this area in 2014 [34]. We assume that the CO₂ emissions are required to decrease by approximately 10% at every master problem time step to a final emission bound of $E_9 = 35000$ tonne.

The uncertainty budget in the subproblem (Λ^w) is 2 meaning that the model can change load in maximum of 2 nodes. Each change the model makes increases load in a node for all operating conditions and subproblem time steps by $\hat{D}_{\tau,n} = 100 \text{ MWh}$.

Parameter	Value
P	1
R	365
$C_{t,u}^x$ Gas (€/MW)	0.8 · 10 ⁶
$C_{t,u}^x$ CCGT (€/MW)	1.0 · 10 ⁶
$C_{t,u}^x$ Oil (€/MW)	0.8 · 10 ⁶
$C_{t,u}^x$ Biomass (€/MW)	3.9 · 10 ⁶
$C_{t,u}^x$ Wind (€/MW)	1.6 · 10 ⁶
$C_{t,u}^x$ Solar (€/MW)	1.8 · 10 ⁶
$C_{t,\ell}^y$ (€)	1.0 · 10 ⁹

TABLE I
INVESTMENT COST PARAMETERS IN THE CASE STUDY

We solve this case study using the Algorithm 1. The results

are show in Table II.

Master problem	Subproblem	Objective value (€)	Solution time (s)
Benders	MIQP	95915334.5162	856.0
MILP	MIQP	95915334.5162	1656.18

TABLE II

Figure 2 shows the evolution of CO₂ emissions to the final desired level during the planning horizon and Figure 3 shows the corresponding CO₂ emission prices. Figures 4 and 5 show the generation and transmission investments, respectively, for achieving the final emission level. Already at $t = 0$, the model builds transmission lines from Finland to Norway and Sweden and a total of 1600 MW of CCGT units in Latvia and Lithuania as well as 1100 MW of wind power in Finland. As a consequence, CO₂ emissions from $t = 0$ to $t = 4$ are below the bounds until demand increases to a high enough level at $t = 5$. To reduce CO₂ emissions to the final level, the model invests in approximately 700 MW of biomass units in Estonia and Finland. These transmission and generation investments allow replacing coal- and oil shale-fired generation with less-polluting wind power as well as gas and biomass-fired generation.

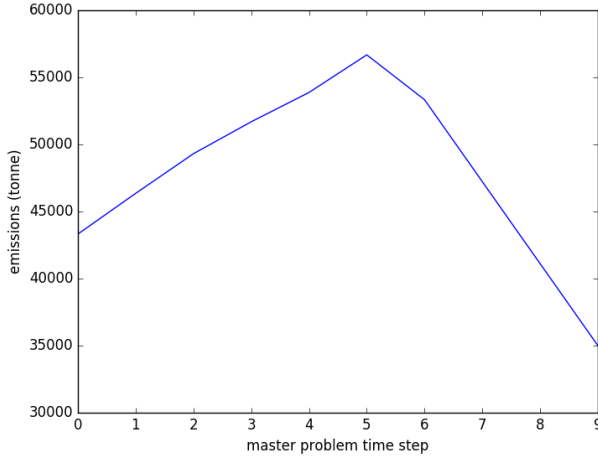


Fig. 2. CO₂ emissions during the planning horizon

IV. CONCLUSIONS

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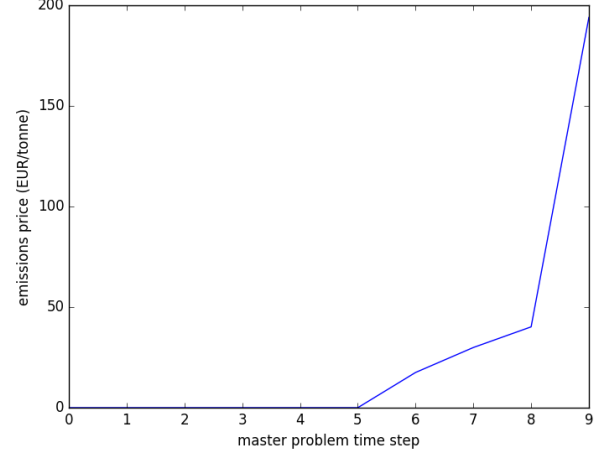


Fig. 3. CO₂ emission prices during the planning horizon

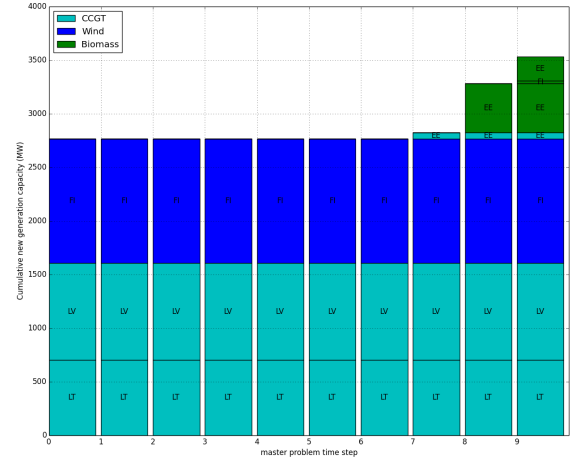


Fig. 4. Generation investments during the planning horizon. The country codes indicate the node where each generation unit is built

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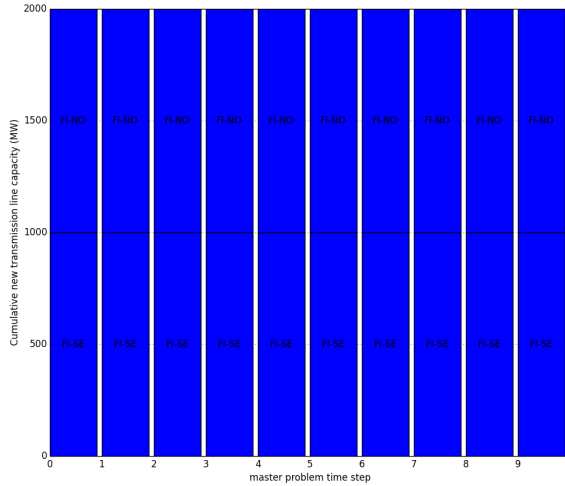


Fig. 5. Transmission investments during the planning horizon. The country codes indicate the start and end node of each line

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