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Renewable energy expansion under taxes and subsidies: A transmission operator's perspective

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ABSTRACT

This paper investigates the role of a transmission system operator within a carbon footprint reduction strategy incorporating carbon taxes and renewable energy generation subsidies in the decentralised energy market. This is achieved via an optimisation bi-level model in which a welfare-maximising transmission system operator makes investments in transmission lines at the upper level while considering power market dynamics at the lower level. To account for the deregulated energy market structure, this paper assumes that the generation companies at the lower level make capacity investments as price-takers in perfect competition. Considering alternative transmission infrastructure expansion budgets, carbon emission taxes and monetary incentives for renewable energy generation capacity expansion, the impact of alternative compositions of these factors is analysed against three output factors: the share of renewable energy in the generation mix, total generation amount, and social welfare. The proposed modelling assessment is applied to an illustrative three-node instance and a case study considering a simplified representation of the energy system of the Nordic and Baltic countries. The results highlight that, under certain circumstances, renewable energy generation subsidies may lead to an increase of renewable energy in the generation mix followed by a simultaneous fall in the total generation amount. Nevertheless, when applied together, these three measures demonstrated a positive impact on all output factors within Nordics' and Baltics' energy systems. The experiments additionally suggest that considering the high value of the carbon tax does not have an impact on the output factors while the composition of high values of renewable energy generation subsidies and budget for transmission infrastructure expansion has the strongest effect.

1. Introduction

The rise in the world's population and associated increasing environmental footprint has underscored the pressing need for global sustainable development. In 2015, the United Nations identified 17 pillars for sustainable development. Taghvaee et al. (2023) suggest that one of the most essential pillars that have an impact on others is global openness and international agreements. A parallel perspective is echoed by Nasrollahi et al. (2020), who attempted to bring the attention of policymakers to international agreements, technological development and energy efficiency emphasising their pivotal role in various sustainable development pillars. This pivotal role of energy efficiency is further underscored by Taghvaee et al. (2022), who highlighted its substantial impact on social welfare, the economy and the environment.

The prospect of ensuring a high level of energy efficiency closely aligns with the need for action to address the alarming effects of climate change. As a response, many European Union (EU) countries have undergone fundamental transformations of their power generation sector to expand the share of low-carbon renewable energy (Wolf et al., 2021; European Commission, 2021; Steffen, 2018; Intergovernmental Panel on Climate Change, 2014). Despite a considerable amount of renewable power that has been installed in the past decade, the vast majority of the EU member countries are far from meeting these levels of variable renewable energy sources (VREs) individually (Redl et al., 2021). Consequentially, a significant amount of renewable energy capacity will be built in the short- and medium-term, requiring large-scale investments.

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However, in liberalised electricity markets, such as those found in EU countries, the UK, and North America, renewable energy revenues are insufficient to provide an adequate return to VRE capacity for private investors (Haar, 2020). Additionally, the increase of the VRE share among the energy sources may jeopardise sufficient power quality (i.e., requirements for uninterrupted power supply and stable conditions of voltage and current), energy systems stability, power balance and efficient transmission and distribution of power (Sinsel et al., 2020). However, existing transmission systems design is not capable of coping with significant levels of renewable penetration (Moreira et al., 2017). Consequentially, renewable-driven expansion of generation requires new approaches for transmission network planning.

The surveys on existing transmission expansion planning literature (Hemmati et al., 2013; Lumbreras and Ramos, 2016; Niharika et al., 2016) suggest the decisions regarding the structure of the power market, the level of detail on the operation of the system and the solution method for the problem to be amongst the key factors defining the distinct approaches. Mathematical optimisation has been extensively applied as a solution method primarily in an academic context as it eradicates the risk of suboptimality of the solution (Lumbreras and Ramos, 2016). However, one should take into account the trade-off between the computational feasibility of solving the problem to optimality and its scale, which in turn is augmented as the modelling detail level and the size of the network modelled increase.

Regarding the representation of deregulation in the power sector, i.e., decoupling transmission and generation expansion decisions, one can pinpoint two generalised strategies in the literature. The first spans investigations aimed at developing an optimal transmission network expansion strategy that would account for various possible developments of the generation infrastructure. Examples of such strategy can be found in Sun et al. (2018), Mortaz and Valenzuela (2019). Nonetheless, while the burden to formulate exhaustive uncertainty sets appears to be challenging on its own, this modelling strategy prevents generation companies (GenCos) from being dynamic market players capable of making reactive decisions regarding generation levels and capacity expansion.

Another strategy attempts to develop efficient modelling tools to consider the planning of the transmission and generation infrastructure expansion in a coordinated manner. For example, this coordinated modelling approach has been considered in Moreira et al. (2017), Tian et al. (2020), Zhang et al. (2020). For the modelling assessment proposed in this paper, we consider a decentralised planning strategy to ensure the representation of the reactive position (i.e., acting as price-takers) of GenCos.

Therefore, this paper aims to study the influence of the transmission system operator (TSO)'s decisions in composition with existing renewables-driven policies, such as carbon taxes and VRE-associated incentives, on the generation mix while assuming the GenCos to behave as price-takers in perfect-competition market settings. It is important to emphasise that these three policies can be considered mechanisms of good governance, which has been shown to play a crucial role in ensuring the efficient management of natural resources (Tatar et al., 2024). Furthermore, this study concentrates on assessing the effectiveness of various policy combinations on the generation mix and social welfare in a decentralised energy market involving generation companies of different scales. To evaluate the impact of the aforementioned renewables-driven policies in the generation mix, applied both separately and together, we propose and utilise a bi-level optimisation model.

The proposed model assumes the TSO to take a leading position and anticipate the generation capacity investment decisions influenced by its transmission system expansion. This assumption leads to the bi-level structure of the proposed model. Such a modelling approach is widely used in energy market planning. As an example, Zhang et al. (2016) exploited a bi-level scheme to consider integrated generation-transmission expansion at the upper level and modified unit-commitment model with demand response at the lower level. Virasjoki et al. (2020) considered a bi-level structure when formulating the model for optimal energy storage capacity sizing and use planning. In this paper, we reformulate the model proposed in Virasjoki et al. (2020) to consider welfare maximising TSO at the upper level, making decisions in the transmission lines instead of energy storage. An analogous strategy has been considered by Siddiqui et al. (2019) during the investigation of the indirect influence of the TSO's decisions as a part of an emissions mitigation strategy aligned with different levels of carbon charges in a deregulated industry. Aimed at the analytical implications, their paper neglects VRE and demand-associated uncertainty, as well as the heterogeneity of the GenCos, while assuming unlimited generation capacity. These shortcomings are addressed in the current paper by means of introducing VRE intermittency and allowing GenCos to invest in diversified power generation technologies. Furthermore, we account for various investment budget portfolios for TSO and GenCos to investigate how GenCos' investment capital availability influences the total VRE share in the optimal generation mix.

This paper evaluates the efficiency of renewables-driven policies by considering a combined transmission and generation investment modelling assessment that involves (1) welfare-maximising TSO at the upper level, (2) heterogeneous GenCos acting under perfect competition at the lower level, (3) uncertainty associated with VRE availability, (4) carbon tax and (5) investment budget constraints to closely represent realistic power system expansion problem. Different levels of the carbon tax and incentives supporting VRE capacity deployment, as well as budget levels allocated for transmission and generation infrastructure expansion, are considered input parameters. The structure of the proposed model allows us to investigate whether TSO's decisions may efficiently foster renewable generation capacity expansion on its own or if it would require other instruments, such as carbon tax and incentives supporting VRE capacity investment. Moreover, we also evaluate the effectiveness of the latter two individually and in combination with the other policies.

The proposed modelling approach allows one to identify optimal strategies for an illustrative 3-node energy system instance and a more realistic energy system replicating the features of Nordic and Baltic countries. In the numerical experiments, a sensitivity analysis is conducted by evaluating the changes in optimal total welfare as well as VRE share in the optimal generation mix and the optimal amount of energy generated. Therefore, the outcome of this research fills in some important knowledge gaps regarding the role of the TSO in a decarbonisation strategy.

The paper is structured as follows. In Section 2, we present the optimisation problem formulations considering centralised and decentralised power market structure. Section 3 presents the primal–dual approach utilised to transform bi-level problems given in Section 2 into a tractable single-level version. In Sections 4 and 5, we evaluate the efficiency of the proposed modelling framework by applying it to two case studies. Section 6 presents conclusions.

2. Problem formulation

In the following sections, we present two alternative formulations of the transmission infrastructure expansion planning problem, considering the centralised and decentralised energy market structure, where the latter is modelled as perfect competition. The notation utilised is described in detail in Appendix C.

2.1. Centralised planning

We begin with a centralised market structure modelled as a single-level problem that is used as a benchmark in this paper. With such a setting, the central planner aims at maximising social welfare by means of making both optimal transmission ($l^+_{n,m}$) and conventional ($g^{e+}_{n,i}$) and renewable ($g^{r+}_{n,i}$) generation capacity investments decisions.

It is important to highlight that pre-existing generation and transmission capacity prior to the beginning of the planning horizon is also accounted for in the modelling setup. The VRE availability is modelled via the consideration of different scenarios $s \in S$ (or operation modes, as sometimes referred to in the literature) and assumptions on the percentage of the total VRE capacity available at each of the nodes considering each of the scenarios and time periods $t \in T$. This value is referred to as the availability factor and denoted as $A^r_{s,t,n}$ for each of the VRE types. Each of the scenarios is weighted with probability P_s such that $\sum_{s\in S} P_s = 1$. The parameter D^e defines the carbon tax (€/MWh) for the conventional generation of type $e \in E$. Likewise, the VRE incentive INC_n is defined for each of the nodes $n \in N$ as the % value that is deducted from the VRE generation capacity investment costs represented by the parameter $I^r_{n,i}$. Therefore, if one, for example, assumed the VRE incentive INC_n to be 10% the GenCos will have to pay 90% of the investment costs associated with the VRE capacity expansion.

With the aforementioned assumptions in mind, the objective function for the centralised planning model can be formulated as follows:

$$\max \sum_{n\in N} \Bigg(\sum_{t\in T}\sum_{s\in S} P_s \left[D^{int}_{s,t,n} q_{s,t,n} - \frac{1}{2} D^{slp}_{s,t,n} \frac{q^2_{s,t,n}}{T_t} - \sum_{i\in I}\sum_{e\in E} \left(C^e_{n,i} + D^e \right) g^e_{s,t,n,i} \right]$$
$$- \sum_{i\in I} \Bigg(\sum_{r\in R} \left[M^r_{n,i} \left(\overline{G}^r_{n,i} + \overline{g}^{r+}_{n,i} \right) + (1 - \frac{INC_n}{100}) I^r_{n,i} \overline{g}^{r+}_{n,i} \right]$$
$$+ \sum_{e\in E} \left[M^e_{n,i} \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) + I^e_{n,i} \overline{g}^{e+}_{n,i} \right] \Bigg)$$
$$- \sum_{m\in N} \left[M^l_{n,m} \frac{1}{2} \left(\overline{L}_{n,m} + l^+_{n,m} \right) + \frac{1}{2} I^l_{n,m} l^+_{n,m} \right] \Bigg). \tag{1}$$

The objective function (1) maximises the total profit for all the GenCos and TSO. The variable $q_{s,t,n}$ represents the demand at node n during time period t and considering scenario s. Therefore, $\forall s \in S,\ t \in T,\ n \in N$ the term $\left(D^{int}_{s,t,n} - \frac{1}{2} D^{slp}_{s,t,n} \frac{q_{s,t,n}}{T_t} \right) q_{s,t,n}$ represents the revenue, where the fist multiplier correspond to the energy price at node n during time period t and considering scenario s.

The conventional and renewable generation capacity expansion decisions ($g^{e+}_{n,i}$ and $g^{r+}_{n,i}$, respectively) along with the transmission lines capacity expansion decisions ($l^+_{n,m}$) are modelled as continuous variables (in MW) restricted by the existing investment budget limits (K^{g+}_i and K^{L+}, respectively) and non-negativity conditions as follows:

$$l^+_{n,m} - l^+_{m,n} = 0 \quad \forall n \in N, m \in N \tag{2}$$
$$\sum_{n\in N}\sum_{m\in N} I^l_{n,m} l^+_{n,m} - K^{L+} \le 0 \tag{3}$$
$$\sum_{n\in N}\sum_{r\in R} I^r_{n,i} \overline{g}^{r+}_{n,i} + \sum_{n\in N}\sum_{e\in E} I^e_{n,i} \overline{g}^{e+}_{n,i} - K^{g+}_i \le 0 \quad \forall i \in I \tag{4}$$
$$\overline{g}^{e+}_{n,i} \ge 0 \quad \forall e \in E, n \in N, i \in I \tag{5}$$
$$\overline{g}^{r+}_{n,i} \ge 0 \quad \forall r \in R, n \in N, i \in I \tag{6}$$
$$l^+_{n,m} \ge 0 \quad \forall n \in N, m \in N, \tag{7}$$

where (2) guarantees the equivalence of the capacity expansion decisions for the transmission lines $n \to m$ and $m \to n$, respectively, $\forall n, m \in N$. It is important to highlight that the continuous nature of the variables representing capacity expansion ($g^{e+}_{n,i}$, $g^{r+}_{n,i}$ and $l^+_{n,m}$) is a simplification needed to limit computational requirements and make feasible the computational experiments performed.

The conventional and renewable generation levels ($g^e_{s,t,n,i}$ and $g^r_{s,t,n,i}$, respectively) are decided considering the following constraints

$$q_{s,t,n} - \sum_{i\in I} \left[\sum_{e\in E} g^e_{s,t,n,i} + \sum_{r\in R} g^r_{s,t,n,i} \right]$$
$$+ \sum_{m\in N: m>n} f_{s,t,n,m} - \sum_{m\in N: m<n} f_{s,t,m,n} = 0 \quad \forall s \in S, t \in T, n \in N \tag{8}$$
$$g^r_{s,t,n,i} - T_t A^r_{s,t,n} \left(\overline{G}^r_{n,i} + \overline{g}^{r+}_{n,i} \right) \le 0 \quad \forall s \in S, t \in T, n \in N, i \in I, r \in R \tag{9}$$
$$g^e_{s,t,n,i} - T_t \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) \le 0 \quad \forall s \in S, t \in T, n \in N, i \in I, e \in E \tag{10}$$
$$g^e_{s,t,n,i} - g^e_{s,t-1,n,i} - T_t R^{up,e}_{n,i} \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) \le 0$$
$$\forall s \in S, t \in T, n \in N, i \in I, e \in E, \tag{11}$$
$$g^e_{s,t-1,n,i} - g^e_{s,t,n,i} - T_t R^{down,e}_{n,i} \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) \le 0$$
$$\forall s \in S, t \in T, n \in N, i \in I, e \in E, \tag{12}$$
$$q_{s,t,n} \ge 0 \quad \forall s \in S, t \in T, n \in N \tag{13}$$
$$g^e_{s,t,n,i} \ge 0 \quad \forall s \in S, t \in T, n \in N, i \in I, e \in E \tag{14}$$
$$g^r_{s,t,n,i} \ge 0 \quad \forall s \in S, t \in T, n \in N, i \in I, r \in R, \tag{15}$$

where constraint (8) ensures the balance between power consumption, generation and transmission, while constraints (9) and (10) define the bounds for the VRE and conventional generation, respectively. Inequalities (11) and (12) represent maximum ramping levels for conventional generation.

The terms $f_{s,t,n,m}$ represent the power flows from node n to node m ($f_{s,t,n,m} > 0$ if node n supplies energy to node m, and $f_{s,t,n,m} = 0$ otherwise) and are constrained by the following set of constraints

$$f_{s,t,n,m} - T_t \left(\overline{L}_{n,m} + l^+_{n,m} \right) \le 0 \quad \forall s \in S, t \in T, n \in N, m \in N \tag{16}$$
$$- f_{s,t,n,m} - T_t \left(\overline{L}_{n,m} + l^+_{n,m} \right) \le 0 \quad \forall s \in S, t \in T, n \in N, m \in N \tag{17}$$
$$f_{s,t,n,m} = 0 \quad \forall s \in S, t \in T, n \in N, m \in N : m \le n, \tag{18}$$

where the equality (18) excludes from optimisation the terms $f_{s,t,n,m}$ where $m \le n$, constraints (16) and (17) define the transmission flows bounds. It is worth highlighting that we opted for simplifying the transmission operation system details for the sake of computational tractability. Therefore, power flow dynamics only takes into account Kirchhoff's first law stating that the sum of currents entering each node should be zero (Quintela et al., 2009) rather than a DC or AC flow model, which ultimately circumvents the computational burden incurred from the need to consider additional control variables (Lumbreras and Ramos, 2016; Padiyar and Shanbhag, 1988).

In the following sections, we separately formulate lower and upper portions of the proposed bi-level optimisation problem representing a decentralised power market structure, as opposed to the centralised structure presented in Section 2.1.

2.2. Lower level: power market operations

The lower level of the proposed bi-level formulation depicts the power market operations under the assumption of having been given the TSO's decisions regarding the capacity of the transmission lines. The modelling setting considers the possibility for each GenCo to own and operate some generation capacity of various technologies at each node $n \in N$ simultaneously and sell the power generated to the market. Hence, each GenCo invests in the additional generation capacity to maximise its revenue.

We assume the market to experience perfect competition, implying that GenCos act as price-takes. Following Gabriel et al. (2013, Section 3.4.2) and considering linear inverse demand functions, we can formulate a single optimisation problem objective function as follows.

$$\max \sum_{n\in N} \Bigg(\sum_{t\in T}\sum_{s\in S} P_s \left[D^{int}_{s,t,n} q_{s,t,n} - \frac{1}{2} D^{slp}_{s,t,n} \frac{q^2_{s,t,n}}{T_t} - \sum_{i\in I}\sum_{e\in E} \left(C^e_{n,i} + D^e \right) g^e_{s,t,n,i} \right]$$
$$- \sum_{i\in I} \Bigg(\sum_{r\in R} \left[M^r_{n,i} \left(\overline{G}^r_{n,i} + \overline{g}^{r+}_{n,i} \right) + (1 - \frac{INC_n}{100}) I^r_{n,i} \overline{g}^{r+}_{n,i} \right]$$
$$+ \sum_{e\in E} \left[M^e_{n,i} \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) + I^e_{n,i} \overline{g}^{e+}_{n,i} \right] \Bigg) \Bigg) \tag{19}$$

s.t.: (4)–(6), (8)–(18).

2.3. Upper-level: transmission infrastructure planning

The formulation of the upper level of the proposed bi-level problem defining the optimal transmission expansion strategy planned by the TSO is given as follows. Considering a proactive TSO's position, it attempts to maximise social welfare through transmission infrastructure expansion, taking into account a given investment capability while anticipating GenCos' reactive generation capacity expansion and operation decisions at the lower level. Hence, the corresponding optimisation problem can be formulated as

$$\begin{aligned}\max_{l^{+}_{n,m}} \sum_{n\in N} \Bigg(& \sum_{t\in T} \sum_{s\in S} P_s \Bigg[D^{int}_{s,t,n} q_{s,t,n} - \frac{1}{2} D^{slp}_{s,t,n} q^2_{s,t,n} \\ & - \sum_{i\in I} \sum_{e\in E} \left(\left[C^e_{n,i} + D^e \right] g^e_{s,t,n,i} \right) \Bigg] \\ & - \sum_{i\in I} \Bigg(\sum_{r\in R} \left[M^r_{n,i} \left(\overline{G}^r_{n,i} + \overline{g}^{r+}_{n,i} \right) + (1 - \frac{INC_n}{100}) I^r_{n,i} \overline{g}^{r+}_{n,i} \right] \\ & + \sum_{e\in E} \left[M^e_{n,i} \left(\overline{G}^e_{n,i} + \overline{g}^{e+}_{n,i} \right) + I^e_{n,i} \overline{g}^{e+}_{n,i} \right] \Bigg) \\ & - \sum_{m\in N} \left[M^l_{n,m} \frac{1}{2} \left(\overline{L}_{n,m} + l^{+}_{n,m} \right) + \frac{1}{2} I^l_{n,m} l^{+}_{n,m} \right] \Bigg) \end{aligned} \tag{20}$$

s.t.: (2)–(3), (7)

and $g^e_{s,t,n,i}, q_{s,t,n}, \overline{g}^{e+}_{n,i}, \overline{g}^{r+}_{n,i} \in \arg\max \{ (19) \text{s.t.:} (4)–(6), (8)–(18) \}$.

3. Single-level representation of the bi-level problem

To solve the proposed bi-level model

$$\max \{ (20), \text{ s. t.: } (2)–(3), (7), \text{ and } g^e_{s,t,n,i}, g^r_{s,t,n,i}, q_{s,t,n}, \overline{g}^{e+}_{n,i}, \overline{g}^{r+}_{n,i} \in \arg\max \{ (19), \text{ s. t.: } (4)–(6), (8)–(18) \} \} \tag{21}$$

we employ a single-level reformulation. In contrast to Virasjoki et al. (2020) who developed a single-level reformulation of an analogous problem based on a mathematical programme with primal and dual constraints approach, we relied on a formulation that yields a mathematical programme with equilibrium constraints (MPEC) (Gabriel et al., 2013), which involves constraints that represent equilibrium conditions. Considering that the lower-level optimisation problem is convex and all the constraints are affine functions, one can replace it with its corresponding Karush–Kuhn–Tucker (KKT) conditions. The KKT conditions, in this context, represent the lower-level problem's optimality conditions. Then, the MPEC comprises the upper-level problem objective function (20) and respective constraints (2), (3) and (7) with constraints representing the KKT conditions for the lower-level problem. Notice that the KKT conditions for the lower-level problem contain primal feasibility constraints (4) – (6), (8) – (18) and the following set of constraints:

$$\begin{aligned} & \nabla_{g^e_{s,t,n,i}} (19) + \theta_{s,t,n} \nabla_{g^e_{s,t,n,i}} (8) + \beta^e_{s,t,n,i} \nabla_{g^e_{s,t,n,i}} (10) \\ & + \beta^{up,e}_{s,t,n,i} \nabla_{g^e_{s,t,n,i}} (11) + \beta^{down,e}_{s,t,n,i} \nabla_{g^e_{s,t,n,i}} (12) - \lambda^e_{s,t,n,i} = 0, \\ & \qquad \forall\ s \in S, t \in T, n \in N, i \in I, e \in E \end{aligned} \tag{22}$$

$$\begin{aligned} & \nabla_{g^r_{s,t,n,i}} (19) + \theta_{s,t,n} \nabla_{g^r_{s,t,n,i}} (8) + \beta^r_{s,t,n,i} \nabla_{g^r_{s,t,n,i}} (9) - \lambda^r_{s,t,n,i} = 0, \\ & \qquad \forall\ s \in S, t \in T, n \in N, i \in I, r \in R \end{aligned} \tag{23}$$

$$\nabla_{q_{s,t,n}} (19) + \theta_{s,t,n} \nabla_{q_{s,t,n}} (8) = 0,\ \forall\ s \in S, t \in T, n \in N, \tag{24}$$

$$\begin{aligned} & \nabla_{\overline{g}^{e+}_{n,i}} (19) + \beta^{g+}_i \nabla_{\overline{g}^{e+}_{n,i}} (4) + \sum_{s\in S} \sum_{t\in T} \beta^e_{s,t,n,i} \nabla_{\overline{g}^{e+}_{n,i}} (10) \\ & + \sum_{s\in S} \sum_{t\in T} \beta^{up,e}_{s,t,n,i} \nabla_{\overline{g}^{e+}_{n,i}} (11) + \sum_{s\in S} \sum_{t\in T} \beta^{down,e}_{s,t,n,i} \nabla_{\overline{g}^{e+}_{n,i}} - \lambda^{e+}_{n,i} = 0, \\ & \qquad \forall\ n \in N, I \in I, e \in E \end{aligned} \tag{25}$$

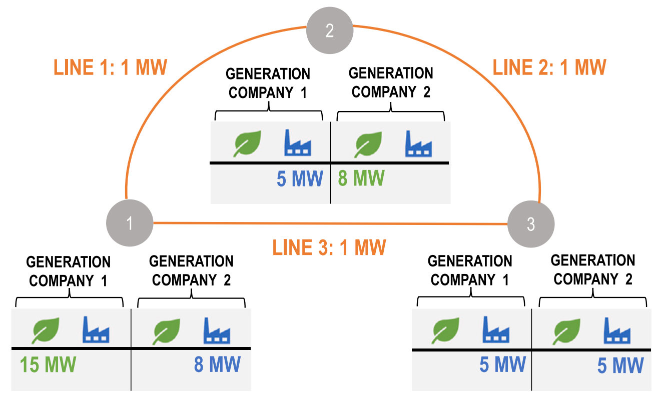

Fig. 1. Illustrative energy system structure.

$$\begin{aligned} & \nabla_{\overline{g}^{r+}_{n,i}} (19) + \sum_i \beta^{g+}_i \nabla_{\overline{g}^{r+}_{n,i}} (4) + \sum_{s\in S} \sum_{t\in T} \beta^r_{s,t,n,i} \nabla_{\overline{g}^{r+}_{n,i}} (9) - \lambda^{r+}_{n,i} = 0, \\ & \qquad \forall\ n \in N, I \in I, r \in R \end{aligned} \tag{26}$$

$$\begin{aligned} & \theta_{s,t,n} \nabla_{f^{s,t,n,m}_{n,i}} (8) + \beta^{f_1}_{s,t,n,m} \nabla_{f^{s,t,n,m}_{n,i}} (16) \\ & + \beta^{f_2}_{s,t,n,m} \nabla_{f^{s,t,n,m}_{n,i}} (17) + \lambda^f_{s,t,n,m} \nabla_{f^{s,t,n,m}_{n,i}} (18) = 0, \\ & \qquad \forall\ s \in S, t \in T, n \in N, m \in N\ :\ m \leq n \end{aligned} \tag{27}$$

$$0 \leq \beta^{g+}_i \perp (4) \leq 0,\ \forall\ i \in I \tag{28}$$

$$0 \leq \beta^r_{s,t,n,i} \perp (9) \leq 0,\ \forall\ s \in S, t \in T, n \in N, i \in I, r \in R \tag{29}$$

$$0 \leq \beta^e_{s,t,n,i} \perp (10) \leq 0,\ \forall\ s \in S, t \in T, n \in N, i \in I, e \in E \tag{30}$$

$$0 \leq \beta^{up,e}_{s,t,n,i} \perp (11) \leq 0,\ \forall\ s \in S, t \in T, n \in N, i \in I, e \in E \tag{31}$$

$$0 \leq \beta^{down,e}_{s,t,n,i} \perp (12) \leq 0,\ \forall\ \ s \in S, t \in T, n \in N, i \in I, e \in E \tag{32}$$

$$0 \leq \beta^{f_1}_{s,t,n,m} \perp (16) \leq 0,\ \forall\ s \in S, t \in T, n \in N, m \in N \tag{33}$$

$$0 \leq \beta^{f_2}_{s,t,n,m} \perp (17) \leq 0,\ \forall\ s \in S, t \in T, n \in N, m \in N \tag{34}$$

$$0 \leq \lambda^{e+}_{n,i} \perp -(5) \leq 0,\ \forall\ n \in N, i \in I, e \in E \tag{35}$$

$$0 \leq \lambda^{r+}_{n,i} \perp -(6) \leq 0,\ \forall\ n \in N, i \in I, r \in R \tag{36}$$

$$0 \leq \lambda^e_{s,t,n,i} \perp -(14) \leq 0,\ \forall\ n \in N, i \in I, e \in E \tag{37}$$

$$0 \leq \lambda^r_{s,t,n,i} \perp -(15) \leq 0,\ \forall\ n \in N, i \in I, r \in R \tag{38}$$

and (18),

where $\nabla_x(\cdot)$ represents a vector whose components are partial derivatives of $\cdot$ with respect to x.

4. Numerical experiments: Illustrative example

In this section, the proposed modelling assessment is conducted by applying it to the first example. The resulting optimal decision policies and their impact on a perfectly competitive market structure are compared with the benchmark model, i.e., the centralised planner optimal strategy. All the models are implemented using the Julia (version 1.3.1) language (Bezanson et al., 2017) utilising the BilevelJuMP.jl package (Garcia et al., 2022) and solved using the commercial solver Gurobi (version 9.0.0) (Gurobi Optimization, LLC, 2020). The source code and data generated for the illustrative three-node and the Nordics case studies are openly available at GitHub repositories (Belyak, 2022a,b).

To be able to conduct a thorough analysis of the optimal investment strategies and generation levels in this section, we first consider a simplified structure for the case study, hereinafter referred to as the illustrative instance. Then in Section 5, we consider a case study for the Nordic region. The structure of the illustrative instance is presented in Fig. 1.

Table 1
Illustrative energy system demand and VRE availability profiles.

Node	VRE availability	Demand profile	Inverse demand function	
			Slope	Intercept
1	Moderate (50%)	Low	0.04	260
2	High (70%)	Low	0.04	260
3	Low (30%)	High	0.0075	195

The illustrative energy system comprises 3 nodes, 3 transmission lines of a capacity of 1MW each and 2 GenCos that own some conventional and/or renewable power capacities at each of the nodes presented in Fig. 1 (green leaf and blue factory images represent VRE and conventional energy sources, respectively). The demand profile at each node, along with the VRE availability factor represented as per cent of the total capacity of the corresponding power plant, are defined in Table 1.

We assume node 3 to have a high-demand profile while the other nodes have low-demand levels. Considering the demand definition through the inverse demand function, the low- or high-demand profiles imply steeper or milder slopes of the function curve, accordingly. The VRE availability factor is moderate and high at nodes 1 and 2, respectively, and low at node 3. For the sake of simplicity, we only assume a single scenario for demand and VRE availability eliminating the stochastic nature of the problem. As for the planning horizon, we consider two consecutive months. To model each month, we multiply hourly data by 720 (i.e., 30 days times 24 h) to scale it to a month's equivalent.

Alternative values for the total transmission capacity expansion budget (TEB), GenCos' generation infrastructure expansion budgets (GEB), and carbon tax and renewable generation incentives are considered. The renewable generation incentive is defined as a percentage of total cost reduction arising from installing additional VRE capacity that is subsidised. We performed a univariate sensitivity analysis to understand the impact of each of these mechanisms taken one at a time. Due to a high number of input parameters under analysis, we assume that the input parameters take the discrete values shown in Table 2, where the symbol "M"("B") stands for million (billion).

For each combination of the input parameters, we analyse the total welfare (the value of the upper-level problem objective function), the share of VRE in the total generation mix and the total generation level, which we refer to as output factors.

4.1. Summary of the results

The results for this illustrative case study have proven ineffective to simply increase the TEB in case the GenCos do not plan significant expenses to expand generation infrastructure, i.e., more than €1B. However, in case such circumstances occur, increasing the TEB leads to an increase in the share of VRE in the total generation mix without dampening the total amount of energy generated. However, the question regarding the effectiveness of such a policy in terms of the ratio between its cost and impact remains.

When VRE generation capacity expansion incentive is the single VRE share-increasing policy being considered, one can notice that the numerical results suggest unstable behaviour in the values of each of the output factors. Depending on the GenCos GEB, the share of the subsidised costs might be required to be significantly high to demonstrate a positive correlation between the VRE share and total welfare. Moreover, while the VRE share and total welfare would experience an increase, the total generation amount might decrease before it starts rising again when the incentive increases (see Figs. 6 and 7). Hence, the policymaker should carefully consider at which level the incentives will not harm total generation. Furthermore, it is essential that policymakers consider the increasing global demand for electricity attributed to the digitalisation and electrification of diverse domains, alongside the expanding industrial output and services sector (Mir et al., 2020).

Applying a carbon tax as a unique renewables-driven policy expectedly allows for an increase in VRE share, which induces a decline in the amount of energy produced and a decrease in total welfare value. However, depending on GenCos' GEB, there might be a threshold in the carbon tax value only after which the anticipated rise of VRE share will occur. Nevertheless, it is worth mentioning that even in the absence of a carbon tax or VRE generation capacity expansion incentives there is a consistent trend favouring renewable energy technologies regarding levelised costs of electricity generation, as compared to power production based on fossil fuels (Timilsina and Shah, 2022).

It is worth highlighting that conducting sensitivity analysis for only one parameter at a time allowed us to obtain detailed information regarding all the phenomena that occurred and significantly simplified the interpretation of the results. Introducing multi-dimensional parameters in sensitivity analysis drastically reduces the possibilities for meaningful inferences. Nevertheless, it allows for investigating the influence of the composition of the input parameters on the output factors. This analysis is conducted in the next Section 5 while applying the proposed method to a realistic case study.

The above results come from the analysis presented in Sections 4.2–4.4. It is worth highlighting that in what follows the results for the markets with the centralised planner and perfect competition are nearly identical. Such phenomenon can be also observed in Virasjoki et al. (2020).

4.2. Transmission infrastructure expansion budget (TEB sensitivity)

The proposed methodology is applied to derive an optimal infrastructure expansion strategy and generation levels considering carbon tax and renewable subsidies to be fixed to 0 € / MWh and 0%, respectively, while the GEB takes discrete values given in Table 2. Meanwhile, we conduct a sensitivity analysis on the TEB considering values given in Table 2. The experiments are replicated for both a centralised planner and perfectly competitive generation markets ((1)–(18) and (21), respectively).

Fig. 2 illustrates the results of the sensitivity analysis on the TEB considering the lowest levels of GEB, i.e., 1M € or 10M € for each of the GenCos, indicated by blue and orange lines, respectively. In the graph, each line's legend contains two values corresponding to the GEB values of GenCo 1 (G_1) and GenCo 2 (G_2), respectively. The results suggest no influence of the TEB value on any of the output factors. Moreover, the optimal investment and generation levels are identical for both centralised and perfectly competitive market structures, which is due to the GEB-associated constraint being binding.

Figs. 3 and 4 illustrate the influence of changing the TEB value on each of the output factors assuming large GEB values and considering centralised and perfect competition settings, respectively.

As can be seen, larger TEB values lead to an increase in the renewable generation share along with the total welfare value, and the effect is magnified with the increase of the GEB. Apparently, there is a very small impact on the total generation. Hence, the sole increase of the transmission capacity without involving other policies leads to substitution for lower-priced VRE generation followed by an increase of the total welfare with a slight decline in the total generation.

Let us consider the case of a €1B GEB for each GenCo and compare the differences in optimal investment and generation portfolios when increasing TEB from €25M to €50M in a perfectly competitive market. The detailed analysis for this particular example is presented in Fig. 5. The arrow in the figure indicates the direction of the power flow. The number with the sign "+" next to it on the left represents the capacity added to the transmission line (in MW). And the number without a sign indicates the total amount of energy transmitted during all time periods through this line (in MWh). The right frame of Fig. 5 demonstrates the relative change in the output factors' values in relation to the values

Table 2
Illustrative case study input parameters.

Input parameter	Discrete values set	
Transmission capacity expansion budget (€)	100K, 1M, 10M, 25M, 50M, 75M, 100M	
Generation infrastructure expansion budget (€)	(GenCo 1: 1M, GenCo 2: 1M), (GenCo 1: 10M, GenCo 2: 10M)	small
	(GenCo 1: 10M, GenCo 2: 1B), (GenCo 1: 1B, GenCo 2: 1B)	large
Carbon tax (€/MWh)	0, 25, 50, 75, 100, 125, 150, 175, 200	
Renewable generation incentives (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	

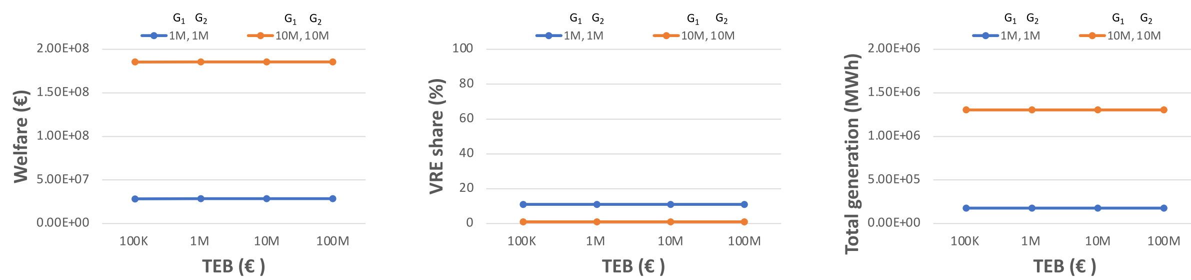

Fig. 2. Sensitivity analysis on the TEB considering the small GEB under centralised and perfect competition settings.

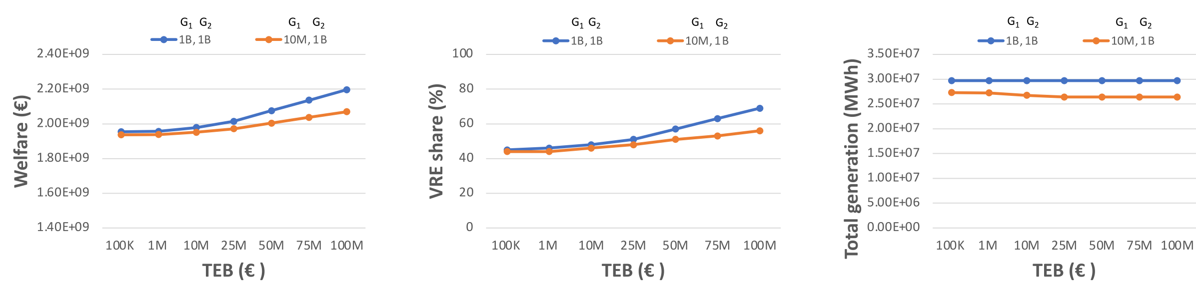

Fig. 3. Sensitivity analysis on the TEB considering the large GEB under centralised planner.

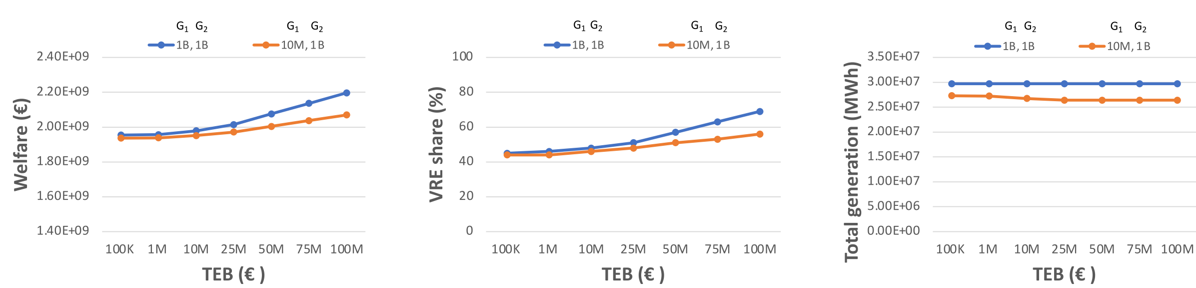

Fig. 4. Sensitivity analysis on the TEB considering the large GEB under the perfectly competitive market setting.

presented on the left. As one can notice, doubling the TEB from €25M to €50M is followed by an increase of 100% in capacity and 99.92% in the flow through the line connecting node 2 (with the highest VRE availability) and node 3 (with the highest demand profile). This transmission capacity expansion motivates GenCos to invest in more VRE generation at node 2, increasing the VRE generation by 19.37% while reducing the conventional generation at node 3 by 11.88%. Ultimately, this new configuration leads to the decrease of GenCos' costs by 3.20% without any decrease in total generation levels. The latter phenomenon, in turn, leads to an increase in the profit by 4.20% and, hence, the increase in the total welfare as well. This illustrates that, even in this stylised example, the model is capable of capturing the key features of the problem regarding the availability of system connectivity and its effect on Gencos' motivation to expand their VRE generation.

4.3. *VRE generation incentives*

Next, the VRE generation-capacity subsidies are varied. Similarly to the previous subsection, we consider the values of the remaining parameters to be fixed. In particular, we assume the carbon tax to remain at 0 € / MWh, the TEB at €10M while considering the GEB values as defined in Table 2 but excluding the case where both GenCos have €1M GEB, due to the similarities in optimal decisions values with the case in which they have the same budget set to €10M.

Figs. 6 and 7 summarise the values of the output factors considering different levels of VRE generation capacity subsidies for the centralised planner and perfectly competitive market, respectively.

The numerical experiments suggest that in cases where the GenCos possess identical GEBs, there is a threshold in the percentage value of VRE subsidies after which the decision to invest in VRE energy becomes

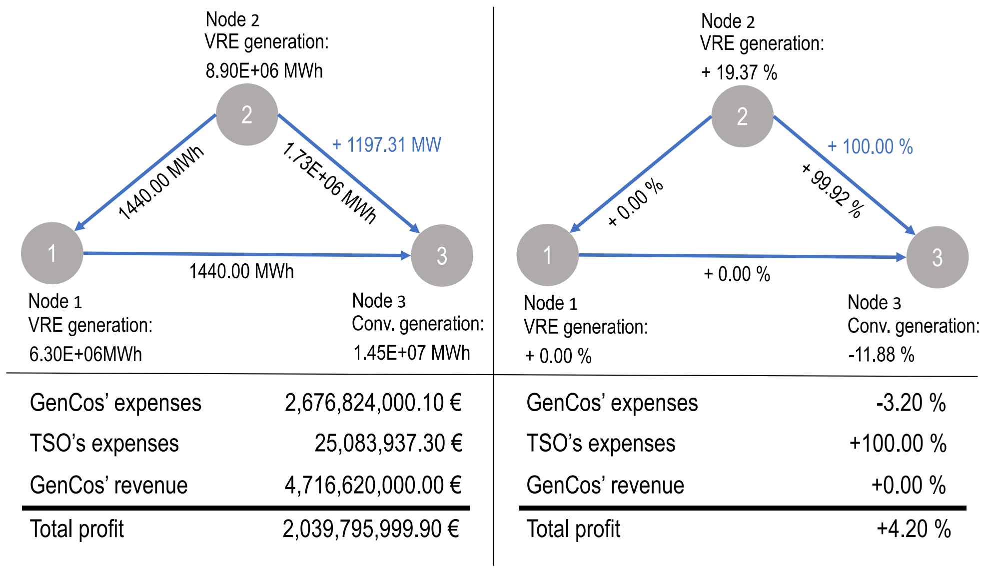

Fig. 5. Differences when considering no incentives, no carbon tax and €1B GEB for each GenCo but changing TEB from €25M (left frame) to €50M (right frame) in perfectly competitive market.

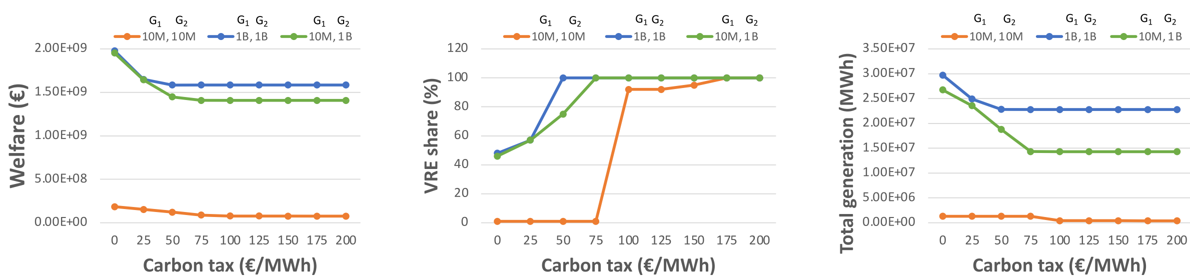

Fig. 6. Sensitivity analysis on the VRE generation capacity subsidies considering different GEB values under centralised planner.

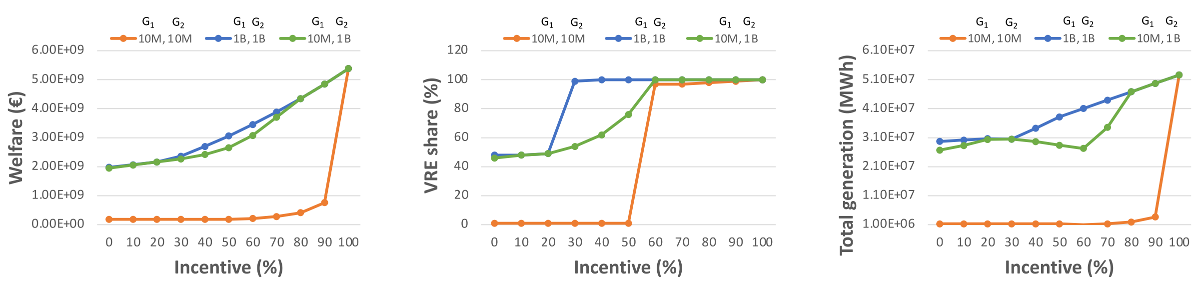

Fig. 7. Sensitivity analysis on the VRE subsidies considering different GEB values in perfect competition.

more appealing (i.e., more profitable) for the GenCos, when compared to conventional generation sources. In particular, for this illustrative example, this value lies between 50% and 60% in the case of lower GEB, i.e., €10M for each GenCo, and between 20% and 30% when this budget is increased to €1B for each GenCo.

Another unanticipated phenomenon observed is the loss in the total generation that occurs when subsidies are between 50% and 60% (30% and 60%; 20% and 30%) of the VRE generation expansion costs for the GenCos with €10M both (€10M and €1B; €1B both) GEB. This is caused by a combination of higher investments in VRE generation capacity and lower generation levels when compared to the case without subsidies. This, in turn, is due to two phenomena. Firstly, the inverse linear dependence between demand and price allows for higher prices when generation levels are lower. Hence, the loss in GenCos' revenues at each node (nodal revenues) is minimised. Secondly, the GenCos experience significant savings in expenses, which compensate the decrease in nodal revenues. For example, Fig. 8 presents a detailed comparison between optimal investment decisions and generation levels considering 50% and 60% incentives for GenCo 1 and GenCo 2 with €10M and €1B GEB, respectively, in case of perfect competition. As one can notice, the increase of subsidies, in this case, stimulates a decrease in conventional generation by almost 100%, which is not completely substituted by VRE generation. However, the fall in GenCos' revenue is compensated by increased nodal prices and overcompensated through reductions in GenCos' expenses by 29.10%, ultimately leading to a profit increase of 15.80%.

4.4. Carbon tax

Lastly, we present a sensitivity analysis for the carbon tax. Similarly to the case of the other input parameters, we fix the values of incentives and TEB budget to 0% and €10M, respectively, while assuming the

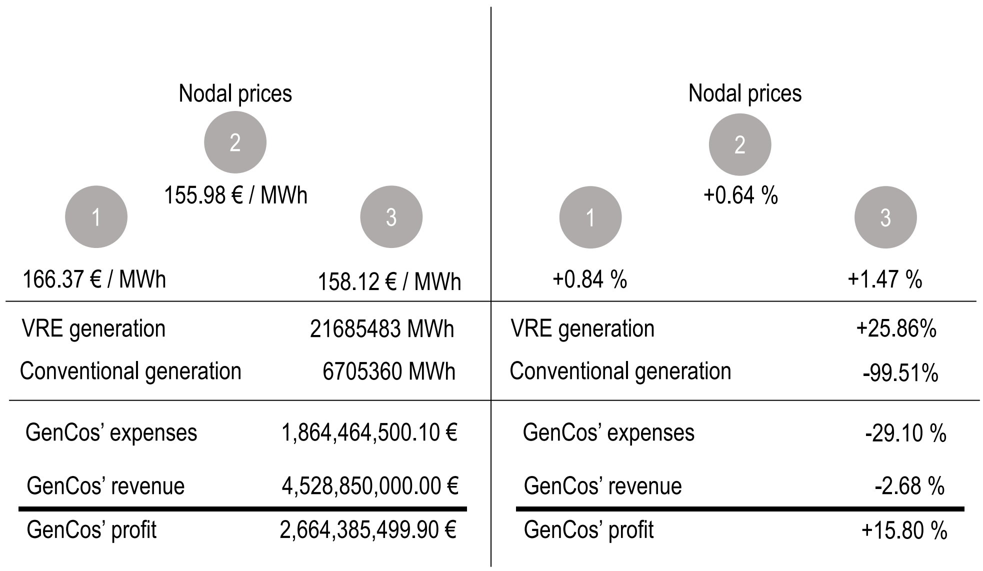

Fig. 8. Differences in optimal results when changing VRE incentive from 50% (left-hand side) to 60% (right-hand side).

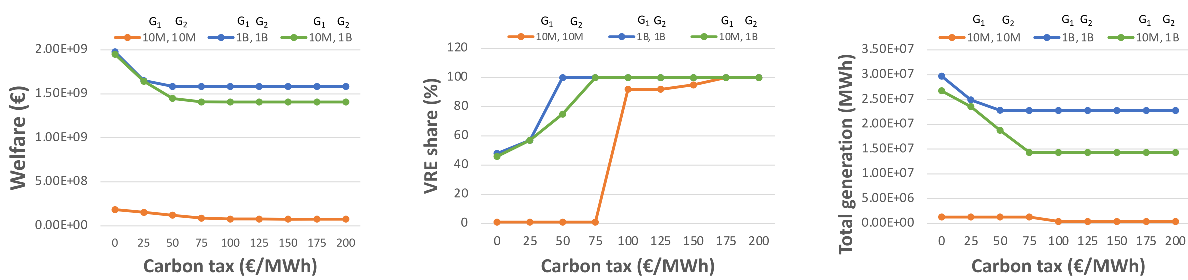

Fig. 9. Sensitivity analysis on the carbon tax considering different budget values for generation capacity expansion under centralised planner.

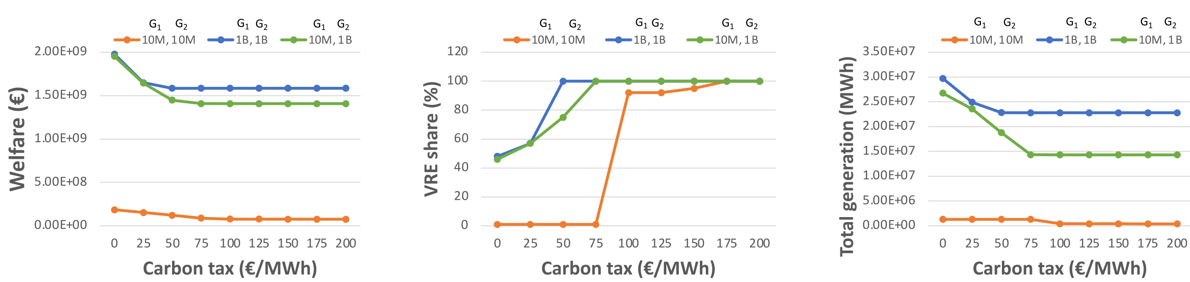

Fig. 10. Sensitivity analysis on the carbon tax considering different GEB values under perfect competition.

GEB to take values from Table 2. Here, we have also omitted the cases in which GenCos have a €1M capacity expansion budget due to the similarities in optimal decision values with the €10M case. We consider the values for the carbon tax to lie within the interval given in Table 2.

Figs. 9 and 10 present the output factors considering centralised and perfectly competitive market structures, respectively. As one can see, the results present a threshold value for the tax, after which it becomes effective and influences the increase of the VRE share in the total mix. This value lies between 75 € / MWh and 100 € / MWh for the GenCos with €10M GEB, and between 0 € / MWh and 25 € / MWh when one or both GenCos posses €1B GEB. Nevertheless, while serving its purpose regardless of the GEB value, the carbon tax causes a decrease in the total generation and, consequently, in the total welfare. Both output factors only remain stable once GenCos cease nearly all the conventional generation (i.e., VRE share in the total generation mix is close to 100%).

5. Numerical experiments: The Nordic energy system case study

Next, we apply the proposed modelling assessment to a system representing the features of the Nordic energy system, enlarged with the Baltic countries grouped as one node. Therefore, the case study system involves 5 nodes representing Finland, Sweden, Norway and Denmark (Nordic countries) and consolidated Estonia, Latvia and Lithuania (Baltic countries), assuming all possible interconnections between these nodes to be potential or existing transmission lines. We conduct an analysis analogous to Section 4 but simultaneously changing different input parameters. The schematic structure of the case study energy system is illustrated in Fig. 11.

For the purpose of simplification, we consider the existence of 5 GenCos, where each is associated with a distinct node (as shown in Fig. 11) and possesses all the generation capacity installed at the corresponding node prior to the beginning of the modelling horizon. This implies that none of the GenCos is assumed to own any preinstalled

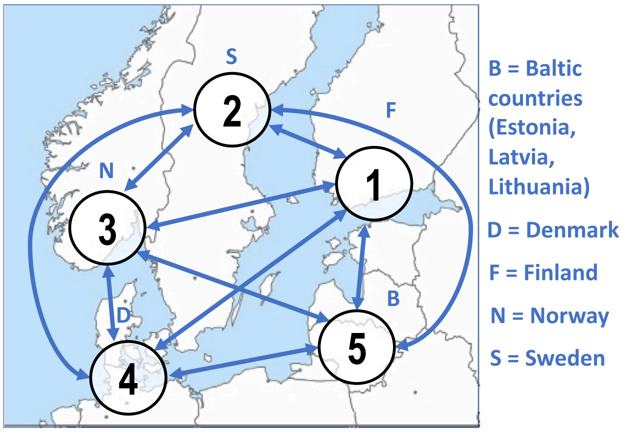

Fig. 11. Case study: Nordics' energy system (d-maps, 2022).

Table 3
Discrete values for the input parameters for the large-scale case study.

Input parameter	"Low" value	"High" value
Transmission capacity expansion budget (€/year)	625M	1.25B
Generation capacity expansion budget (per GenCo, €/year)	3B	6B
Carbon taxes (€/ton of CO_2)	8	71
Renewable generation incentives (%)	5	20

generation capacity at other nodes. Nevertheless, we assume that each of the GenCos may invest in the generation capacity at any node. This assumption is based on the illustrative fact that Finnish energy generation company Fortum operates in several countries, such as Finland, Sweden, Norway, Poland, Germany, Denmark, India and others (Fortum, 2022). Additionally, we enlarge the set of conventional energy sources by considering nuclear energy, open-cycle and combined-cycle gas turbines (OCGT and CCGT, respectively), coal and biomass. As VRE sources, we consider solar as well as onshore and offshore wind. We also account for the hydropower capacity in these countries, though we assume they cannot be expanded.

5.1. Data

All the data for demand, energy prices, installed generation capacity, VRE availability and transmission parameters were gathered from various sources, with information ranging from the years 2018 to 2020. One can refer to Appendix D for more information regarding the data.

Input parameters. Due to the large-scale nature of the case study instance and the consequent computational challenges we have faced, we limited the range of the values for each of the input parameters to a discrete set with two values in the sensitivity analysis. The first one represents a possible "low" value, and the second one represents a "high" value for a corresponding parameter. Therefore, we solve the case study instance for each possible set of 4 input parameters where each parameter takes one of two possible values from a corresponding set which leads to solving 16 different instances in total. The values for the parameters are presented in Table 3. It is worth mentioning that the data for the TEB and GEB is presented for an annual time frame. More information on the procedure for generation input parameter values can be found in Appendix D.

Numerical issues with large-scale MPEC. Despite being able to solve the illustrative instance presented in Section 4, the state-of-the-art mathematical optimisation solvers we tested were unable to solve this more realistic instance. We experimented with different complementary slackness reformulation options and primal–dual equality reformulation available in the BilevelJuMP.jl package (Garcia et al., 2022) along with reductions in the instance size. However, trying to solve a simplified instance with Gurobi v.9.5.0 (Gurobi Optimization, LLC, 2020) or CPLEX v.12.10 (IBM, 2021) within 48 h did not lead to a solution with integrality gaps lower than 100%. An analogous issue has been faced by Virasjoki et al. (2020) where the authors were not able to solve their large-scale mixed-integer quadratically constrained quadratic programming problems with any of the state-of-the-art solvers available in GAMS (GAMS, 2023).

Therefore, following the solution approach proposed in Virasjoki et al. (2020), we applied an iterative procedure in which we discretise and exhaustively enumerate and fix all possible upper-level decisions and solve the lower-level problem. Then, we determine ex post the decisions that yield optimal solutions. The discrete values we considered for the capacity expansion of the transmission lines are {0 MW, 3000 MW, 6000 MW, 9000 MW}. Taking into account the existence of 10 transmission lines in the system, the aforementioned enumerative set leads to 1,048,576 lower-level problems that must be solved for each combination of the input parameters.

Representative days. In light of the large number of lower-level problems to be solved for each set of input parameter values, we considered 3 scenarios and 4 time periods. Hence, each scenario spans a group of 3 representative days corresponding to the demand profile, solar and wind availability, respectively. And the day (24 h) timeline is equally divided into four 6-hour time periods. The idea is inspired by Li and Pye (2018), who used 16 time slots (four diurnal times-slices in four seasons) to model a year for the energy system. Lind and Espegren (2017) used a similar approach for TIMES-Oslo and TIMES-NORWAY models. Additionally, Fodstad et al. (2022) mentioned other authors who used representative daily time slots as a part of the modelling.

To derive representative days, we used hierarchical clustering (Teichgraeber et al., 2019) for the hourly data (8760 h) spanning the time series for demand, wind and solar PV power production for each of the nodes. We highlight that all the data has been normalised, implying that each element of the 3 data sets obtained a value between 0 and 1, where 1 refers to the highest regional demand in the case of the demand-related data. For the solar PV and wind production data sets, the normalisation values are based on the installed capacities, and hence the assigned normalised values never reach 1. When conducting the hierarchical clustering, no weights have been considered between the data time series. The representative days for each cluster have been selected for each data set to most closely approximate the medoid of a cluster. The allocation of weights between the clusters, as well as the distribution of representative days for each cluster and node, are presented in Appendix A. For example, scenario one for Finland has a weight of $\frac{145}{365}$ and is represented by a set of days $\{43, 12, 12\}$ corresponding demand profile, wind and solar availability, respectively. It is important to highlight that the notions of clusters and the weights associated with clusters are used in this context to represent the scenarios and the scenario probabilities, respectively, denoted by $s \in S$ and $P^s, \forall s \in S$.

5.2. Numerical results

Table 4 presents the summary regarding the compositions of the input parameter values that have the strongest and the weakest effect on each of the output factors (VRE share in the generation mix, total welfare and generation amount). Additionally, it provides the relative values indicating the improvement of the corresponding factor compared to its optimal value in case all the input parameters, i.e., carbon tax, VRE incentives, TEB, and GEB are zero (baseline case). It is worth highlighting that the "baseline" case does not closely reflect reality, as these input parameters are greater than zero in practice. Fig. 12

Table 4
Nordics case study: summary. Percentage values (%) are calculated relative to the baseline case.

Small GEB						
	VRES		Welfare		Generation amount	
Largest effect	Low tax High incentive High TEB	+ 42.28%	Low tax High incentive High TEB	+ 66.75%	Low tax High incentive High TEB	+ 105.41%
Smallest effect	Low tax Low incentive Low TEB	+ 28.00%	Low tax Low incentive Low TEB	+ 58.69%	Low tax Low incentive Low TEB	+ 99.94%
High GEB						
	VRES		Welfare		Generation amount	
Largest effect	Low tax High incentive High TEB	+ 56.04%	Low tax High incentive High TEB	+ 78.32%	Low tax High incentive High TEB	+ 165.24%
Smallest effect	Low tax Low incentive Low TEB	+ 53.32%	Low tax Low incentive Low TEB	+ 71.05%	Low tax Low incentive Low TEB	+147.43%

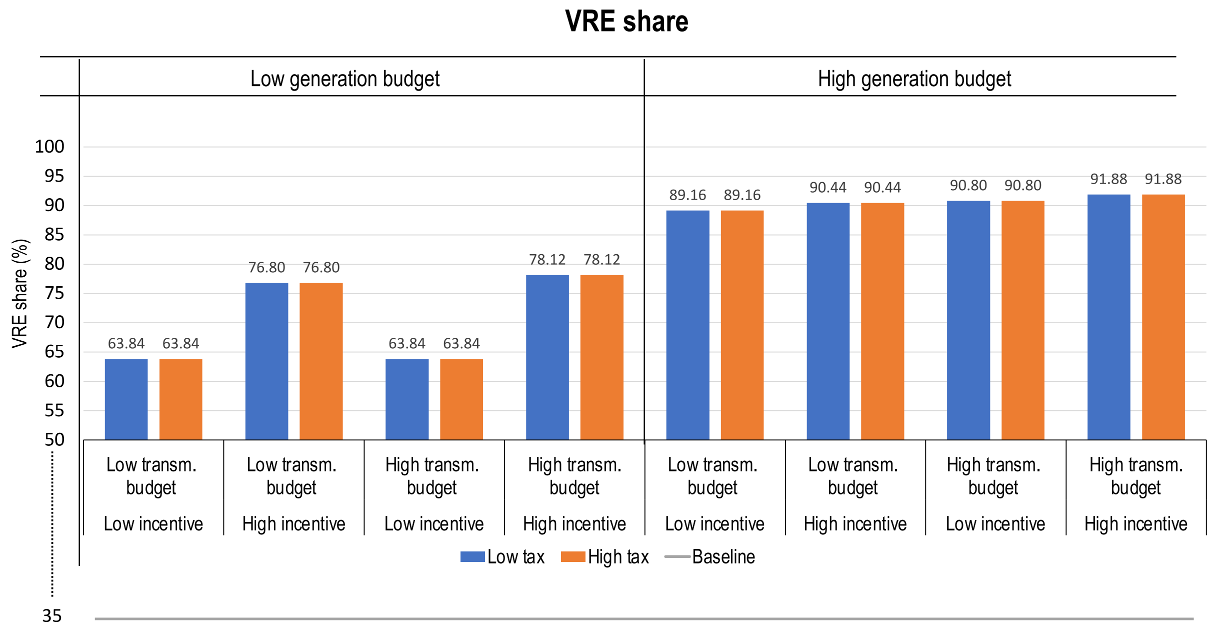

Fig. 12. Case study: Impact of carbon taxes on VRE share.

presents the optimal share of VRE in the generation mix for different combinations of input factors. The bars indicate the share of VRE when the parameter values are “low” or “high” according to Table 3. The “baseline” shows the value of VRE in the optimal generation mix when maximising the total welfare and considering all the input parameters to be zero. Figs. 13 and 14 present relative differences in total welfare and generation values, respectively, for different compositions of the input parameters when compared to the case when all of the parameters are set to zero, i.e., no policies are involved. It is worth highlighting that while all the information regarding output results can be obtained from Figs. 12–14, the primary purpose of these figures is to demonstrate the change in output factors values considering different values of distinct input parameters. In particular, in the case of Fig. 12, this parameter is a tax value, while Figs. 13 and 14 primarily demonstrate information regarding incentive values. The remaining alternative visualisations of the output data is presented in Appendix B.

It is important to bear in mind that the Nordic energy system has a low carbon footprint in 2018–2020. Nordic Energy Research (Nordic Energy Research, 2022) indicates that the Nordics have reached about a 55.00% renewable energy share in the generation mix in 2019. As the numerical results suggest, the optimal generation mix for combined Nordic and Baltic countries has about 35.84% share of VRE when GEB and TEB are set to zero, and no carbon tax nor incentive are involved (baseline case). The results in Fig. 12 demonstrate that using the “worst” composition of the input parameters values, i.e., “low” values for incentive, carbon tax and TEB, one can increase the share of VRE by about 28.0% (that is, from 35.84% in the baseline case to 63.84%) compared to the case with no policies involved for the GenCos with “low” GEB and by about 53.3% (i.e., 89.16–35.84 = 53.32%) for the GenCos with “high” GEB. At the same time, Figs. 13 and 14 indicate that with the “low” values of the input parameters, the total generation and welfare values increase by roughly 99.9% and 58.7%, respectively, for the GenCos with a “small” GEB and by roughly 147.4% and 71.1%, accordingly for the GenCos with “high” GEB, compared to the baseline case.

Figs. 12–14 also suggest that further increasing the carbon tax does not lead to any meaningful improvement regardless of the GEB value that GenCos possess. Potentially, this is because the VRE share in the generation mix has already exceeded 50%. Hence, even if the expenses for the remaining share of the conventional generation rise, its impact on Gencos’ profit is not crucial enough to motivate GenCos to change their investment decisions.

One can also consider the increase of the GEB as a renewables-driven policy. As Figs. 12, and 14 suggest, by only increasing the GEB

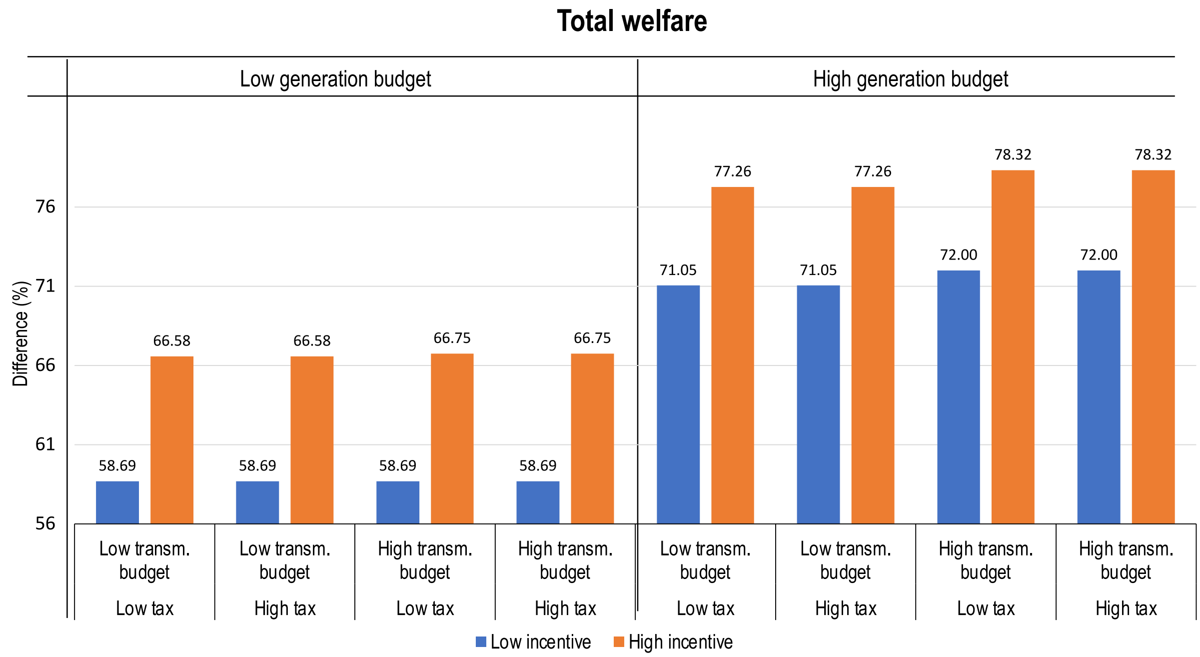

Fig. 13. Case study: Impact of VRE investment incentive on welfare.

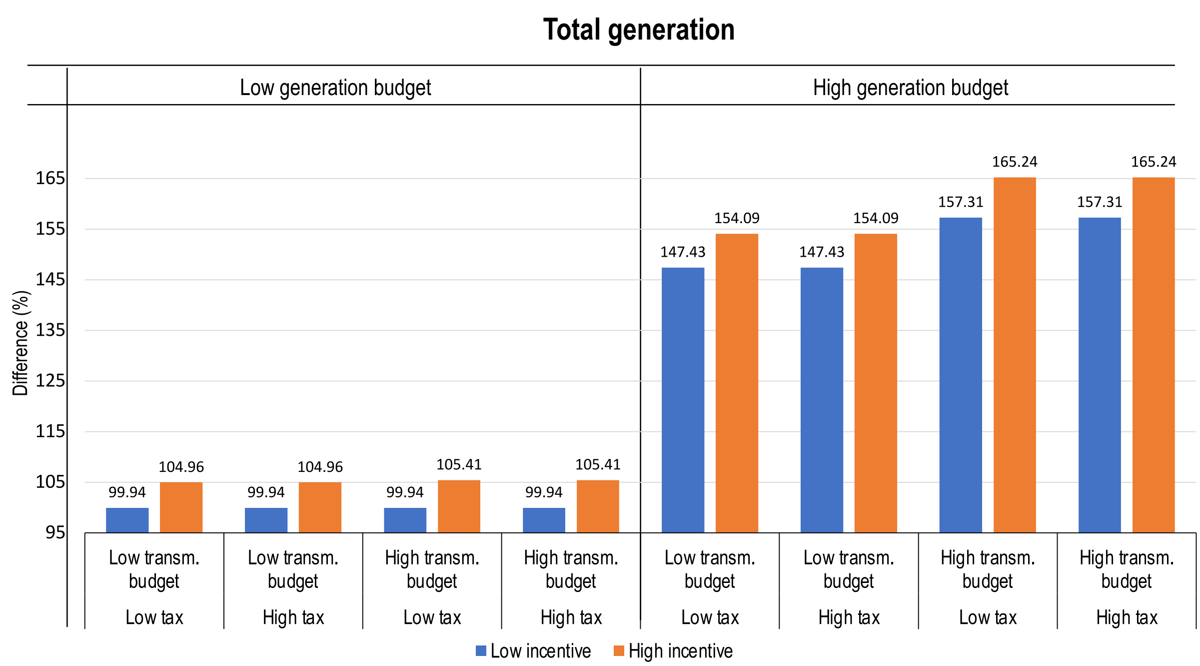

Fig. 14. Case study: Impact of VRE investment incentive on total generation.

value from "low" to "high" while considering the rest of the input parameters (TEB, incentive and carbon tax) at a "low" values, one can increase (compared to the baseline case) the VRE share in the total generation mix by about 25.3% (89.16–63.84 = 25.32%) and the total generation amount by roughly 47.5% (147.43–99.94 = 47.49%) compared to the case of "low" GEB. However, the effect of such an approach on the total welfare is more modest as Fig. 13 reports an increase of welfare (compared to the baseline) that is only about 12.4% (71.05–58.69 = 12.36%) higher than in the case with "low" GEB. The latter is due to the linear dependence between the demand and energy price, leading to the higher generation amount in case of higher GEB value and lower market price.

The two remaining input parameters that have an impact on the output factors under certain circumstances are the TEB and the VRE incentive. We first concentrate on the case when GEB is "low". Figs. 12–14 suggest that doubling the "low" TEB value does not impact any of the output factors if applied alone while the rest of the input parameters remaining at "low" values. Meanwhile, Fig. 12 reports an increase (compared to the baseline) of VRE share in total generation mix by about 13.0% (76.80–63.84 = 12.96%) more than in the case with all "low" input parameters if one was to only increase the VRE incentive value from "low" to "high". Nevertheless, as Figs. 13 and 14 suggest, the impact of solely increasing the incentive value from "low" to "high" has a minor effect on the welfare and total generation values. The numerical experiments suggest that the increase (compared to the baseline) in total welfare and generation amount values is only higher by 7.9% (66.58–58.69 = 7.89%) and 5.0% (104.96–99.94 = 5.02%), respectively than in the case with all “low” input parameters values. Additionally, Figs. 12–14 suggest that considering the simultaneous increase of incentive and TEB values brings up an increase (compared to the baseline) of VRE share, total generation amount and total welfare that is higher by about 14.3% (78.12–63.84 = 14.28%), 5.5% (105.41–99.94 = 5.47%) and 8.1% (66.75–58.69 = 8.06%), respectively, than in the case when all the input parameters are at the “low” values.

In the case of the GenCos possessing “high” GEB, the inference regarding the effect of TEB and incentive on the output factor slightly changes. First of all, Figs. 12–14 suggest that in case of “high” GEB, solely increasing TEB value while keeping the incentive and the tax at the “low” values impacts all of the output factors. The increases (compared to the baseline) in VRE share, total generation amount and total welfare are higher by about 1.6% (90.80–89.16 = 1.64%), 9.9% (157.31–147.43 = 9.88%) and roughly by 1.0% (72.00–71.05 = 0.95%), respectively, than in the case with all (but the GEB) input parameters being at the “low” values. Increasing only the incentive value from “low” to “high” in the presence of the “high” GEB value and the rest of the input parameters being at the “low” values suggests a similar effect as in the case of solely increasing the ”TEB” value. Figs. 12–14 suggest the increase (compared to the baseline) of the VRE share, total generation and total welfare is higher by about 1.3% (90.44–89.16 = 1.28%), 6.7% (154.09–147.43 = 6.66%) and 6.2% (77.26–71.05 = 6.21%), respectively, compared to the case when all the parameters (but the GEB) are “low”. The simultaneous increase of TEB and incentive values considering “high” GEB value leads to the strongest increase in all the output parameters when compared to the baseline. Figs. 12–14 report the increase (compared to the baseline) of VRE share, welfare, and total generation is higher by about 2.7% (91.88–89.16 = 2.72%), 7.3% (78.32–71.05 = 7.27%) and 17.8% (165.24–147.43 = 17.81%), respectively than in the case with all (but the GEB) parameters being “low”.

5.3. Summary of the results

To conclude, the numerical results have shown that the “low” value of the carbon tax presented in Table 3 is efficient enough as the further increase of its value does not lead to an improvement in any of the output factors. Nevertheless, in case GenCos possess a “low” GEB, considering “low” values for TEB and an incentive leads to an increase by about 28.0% in the VRE share in the optimal generation mix when compared with the baseline. At the same time, one can notice an increase by about 58.7% in total welfare and an increase by roughly 99.94% in total generation amount. If one is aimed at maximising VRE share, welfare and total generation values, one should consider simultaneously increasing TEB and incentive values to “high”. Such an approach leads to an increase (compared to the baseline) of VRE share, welfare and total generation values, which is higher by about 14.3%, 8.1% and 5.5%, respectively, than in the case if all the input parameters are “low”. However, one should bear in mind that the numerical results suggest that “high” incentive value has a greater influence on VRE share and welfare increase if applied solely compared to only increasing TEB value.

In case GenCos possess a “high” GEB exploring “low” values of all the input parameters leads to an increase by about 53.3%, 71.1% and 147.4% in VRE share, welfare and generation amount, respectively, when compared to the baseline results. Further increasing TEB and incentive to “high” values allows one to obtain the highest values for all the output factors. The results show an increase (compared to the baseline) of VRE share, welfare and generation amount that is higher by about 2.7%, 7.3% and 17.8%, respectively, than in the case with all (but the GEB) input parameters being at the “low” value. Meanwhile, the results also suggest that if one was to solely increase just either TEB or incentive value, then the choice should be made in favour of TEB in case the aim is to increase the total generation amount or VRE share in the total generation mix. Alternatively, only increasing incentive value would have a greater impact on welfare than solely increasing TEB value when compared to the optimal welfare value for the case with all (but the GEB) parameters being at a “low” value.

6. Conclusions

In this paper, we study the impact of the TSO infrastructure expansion decisions in combination with carbon taxes and renewable-driven investment incentives on the optimal generation mix. To examine the impact of renewables-driven policies we propose a novel bi-level modelling assessment to plan optimal transmission infrastructure expansion. At the lower level, we consider a perfectly competitive energy market comprising GenCos who decide optimal generation levels and their own infrastructure expansion strategy. The upper level consists of a TSO who proactively anticipates the aforementioned decisions and decides the optimal transmission capacity expansion plan. To supplement the TSO decisions with other renewable-driven policies, we introduced carbon taxes and renewable capacity investment incentives in the model. Additionally, we accounted for variations in GenCos’ and TSO’s willingness to expand the infrastructure by introducing an upper limit on the generation (GEB) and transmission capacity expansion (TEB) costs. Therefore, as the input parameters for the proposed bi-level model, we considered different values of TEB, GEB, incentives and carbon tax. This paper examined the proposed modelling approach by applying it to a simple, three-node illustrative case study and a more realistic energy system representing Nordic and Baltic countries. The output factors explored in the analysis are the optimal total welfare, the share of VRE in the optimal generation mix and the total amount of energy generated.

In the illustrative case study, each of the parameters has been individually tested on a wide range of discrete values. The numerical experiments revealed the inefficiency of attempting to distinctly increase the budget allocated for transmission infrastructure expansion in case GenCos do not plan significant generation capacity expansions. Moreover, even when the generation expansion budget is large, the trade-off between the increase of VRE share and transmission infrastructure investment costs still poses the question of whether such a policy is efficient. Furthermore, the experiments identified difficulties in qualifying the impact of increasing the VRE capacity expansion incentives on each of the output factors due to the inconsistencies in the output data. However, the increase in carbon taxes has demonstrated a straightforward connection with the increase in VRE share once the marginal value of conventional energy becomes less profitable for GenCos.

The numerical experiments for a more realistic case study depicting Nordic and Baltic countries’ energy systems indicated the largest increase in all the output factors when compared to the case with no policies involved (i.e., when GEB, TEB, carbon tax and incentive are zeros) if one was to consider “high” values of TEB and incentive and “low” value for carbon tax regardless of the GEB value. However, the extent of increase in the values of all output factors followed by changing values of TEB and incentive from “low” to “high” varies depending on the GEB value. Therefore, the results indicate the prominent role of the TSO in the renewable transition of the energy market.

It is worth mentioning that to ensure the computational tractability of the proposed model, we allowed for a number of simplifications in the modelling approach. In particular, our model does not account for an intranodal spatial resolution. Therefore, the estimates derived from the proposed modelling methodology should be considered as an initial approximation, and further refinement may be necessary for practical implementation. In particular, the simplifications we considered are (i) considering only Kirchhoff’s voltage law, (ii) lack of account for revenue streams for the TSO and (iii) simplification of planning horizon and truncation of the scale of uncertainty representation. Nevertheless, the aforementioned simplifications do not diminish policy-related insights concluded from the numerical experiments. In addition, applying the proposed modelling assessment to the case study representing Nordic and Baltic countries' energy systems revealed the limitations associated with solving such instances using state-of-the-art solvers. Therefore, we discretised and enumerated possible upper-level decisions and afterwards, among all the possible alternatives, they determined the investment portfolio maximising the welfare. For the input parameters, we considered two types of values named "low" and "high" in accordance with open data regarding Nordic GenCos and TSO's infrastructure expansion investments plans and current EU member's carbon taxation systems.

Regarding further research, one could pinpoint a few possible directions. The first one is related to considering an imperfectly competitive market defining a Cornout oligopoly (Ruffin, 1971) instead of perfect competition. The imperfectly competitive market structure may more closely represent the reality (Oikonomou et al., 2009) as the oligopolies have access to information helping them in the decision-making process. However, this would require formulating a set of separate subproblems for each of the GenCos at the lower level which would further increase the computational burden. An alternative avenue for future research could involve the integration of storage batteries into the grid. This would potentially alleviate the intermittency problem regarding the availability of variable renewable energy sources and hence provide new insights, thereby offering novel perspectives on the outcomes of numerical experiments. However, one should bear in mind that this would also most probably further complicate the computational tractability of the problem. Another possible enhancement could stem from the development of an efficient solution method that allows one to consider a continuous range of investment decisions for the TSO at the upper level. Lastly, if the modelling simplifications caused by limitations of state-of-the-art solvers are overcome one could investigate how policy-related insights differ in case the model allows for a higher level of detail for energy system representation, investment projects, uncertainty formulation and the planning horizon.

CRediT authorship contribution statement

Nikita Belyak: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Steven A. Gabriel:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Nikolay Khabarov:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Fabricio Oliveira:** Writing – review & editing, Supervision, 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

All data and code available in a repository cited in the text.

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Table 5
Representative days for each of the clusters and nodes.

Node	Cluster 1 weight: $\frac{145}{365}$	Cluster 2 weight: $\frac{117}{365}$	Cluster 3 weight: $\frac{103}{365}$
Finland	demand: day 43 wind: day 12 solar: day 12	demand: day 263 wind: day 257 solar: day 257	demand: day 177 wind: day 204 solar: day 200
Sweden	demand: day 12 wind: day 10 solar: day 6	demand: day 257 wind: day 320 solar: day 91	demand: day 204 wind: day 199 solar: day 159
Norway	demand: day 12 wind: day 12 solar: day 6	demand: day 257 wind: day 257 solar: day 77	demand: day 204 wind: day 204 solar: day 210
Denmark	demand: day 12 wind: day 354 solar: day 313	demand: day 257 wind: day 257 solar: day 104	demand: day 204 wind: day 204 solar: day 200
Baltics	demand: day 26 wind: day 88 solar: day 323	demand: day 267 wind: day 258 solar: day 89	demand: day 190 wind: day 141 solar: day 150

Appendix A. Hierarchical clustering

See Table 5.

Appendix B. Alternative representations of the output data for nordics case study

Figs. 15–20.

Appendix C. List of nomenclature

Tables 6–12.

Appendix D. Numerical experiments: The data for the Nordic energy system case study

To gather input data regarding demand and energy prices, we utilised the ENTSO-E Transparency Platform (Hirth et al., 2018). Assuming each Nordic country was represented by one node, we had to aggregate price zones in some countries. For that, we accumulated the demand for all price zones in the country and calculated an average value for the energy price.[1] We performed the same aggregation for the Baltic countries.

We also used the ENTSO-E Transparency Platform to gather the data regarding the preinstalled generation capacity at each node. Analogously, we accumulated generation capacity by combining all price zones when necessary. Given the lack of information on the distribution of gas sources between open- and combined-cycle gas turbines, we

[1] We considered a simple moving average, i.e., the average price over the specified period. However, one could use other available alternatives, e.g., a volume-weighted average (John, 1999).

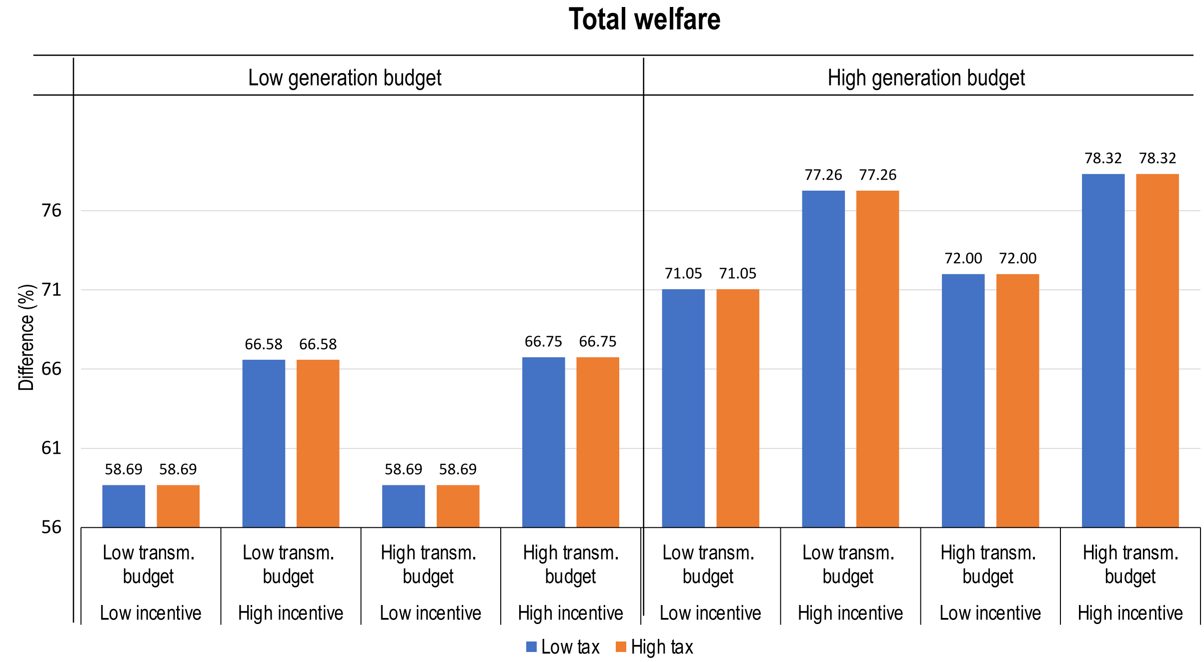

Fig. 15. Case study: Impact of carbon taxes on welfare.

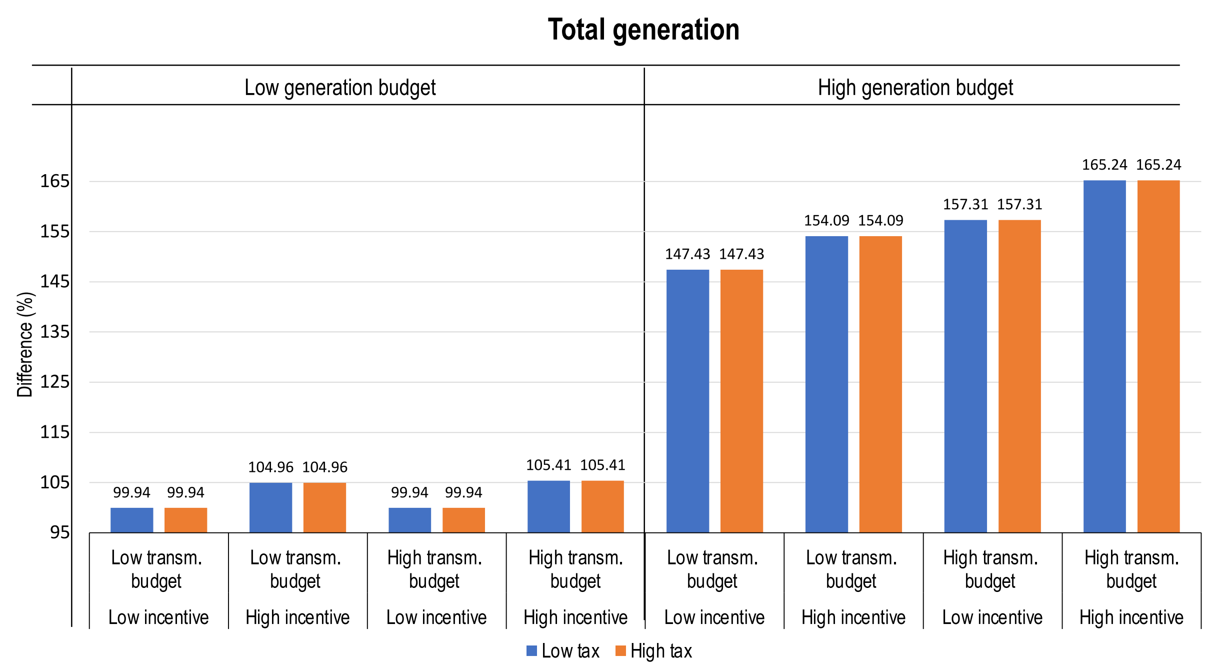

Fig. 16. Case study: Impact of carbon taxes on total generation.

Table 6
General parameters.

Symbol	Description	Units
T_t	Number of hours clustered for the time period $t \in T$	h
P_s	Probability of the availability scenario $s \in S$	
$D^{slp}_{s,n,t}$	Slope of linear inverse demand function at scenario $s \in S$, node $n \in N$ in time period $t \in T$	€/MWh^2
$D^{int}_{s,t,n}$	Intercept of linear inverse demand function at scenario $s \in S$, node $n \in N$ in time period $t \in T$	€/MWh
K^{g+}_i	Generation capacity expansion investment budget for the producer $i \in I$	€

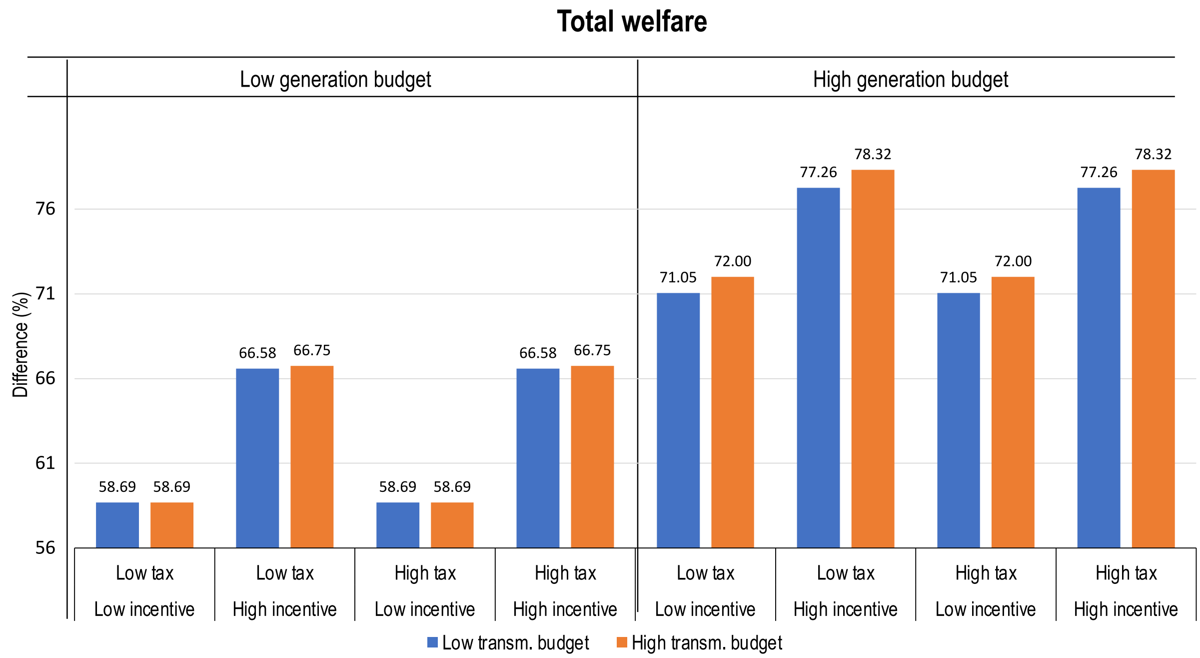

Fig. 17. Case study: Impact of transmission capacity expansion budget on welfare.

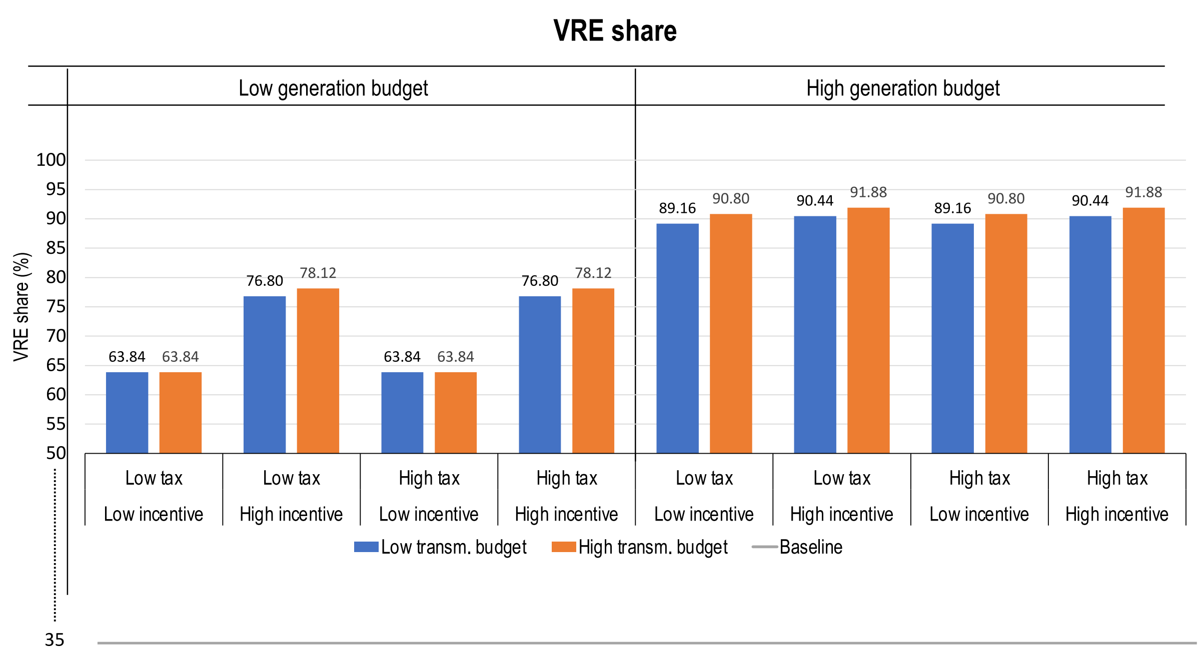

Fig. 18. Case study: Impact of transmission capacity expansion budget on VRE share.

assumed an equal share between them. Regarding the investment, variable operational, fixed maintenance and fuel costs, as well as the lifetime values for each of the energy sources but coal, we referred to Kan et al. (2020). All the cost values for the coal are defined as in Chatzimouratidis and Pilavachi (2009) while the lifetime was assumed to be 50 years in accordance with (Cui et al., 2019). The values for the ramping levels regarding conventional energy sources are specified as in Rintamäki (2022). The VRE availability factor represented as the share of the total installed capacity was defined following (Condeixa et al., 2022).

We also accumulated all the data regarding hydropower generation capacity, including pumped storage, run-of-rivers and reservoirs provided by the ENTSO-E Transparency Platform. For the sake of simplicity, we assumed the hydropower capacity to be specified annually, implying that the hydropower reservoirs are refilled by the beginning of the next year. Another assumption involves the equal distribution of the total hydropower capacity among the time periods and scenarios.

The transmission line investment costs, fixed maintenance costs and lifetime were specified as in Kan et al. (2020). The installed transmission capacities were set according to Nycander et al. (2020). We accumulated transmission capacity for all connected price zones to define transmission line capacity between two nodes. Considering the cases when the transmission line allows for different voltages at the ends, to define a uniform capacity value, we considered an average

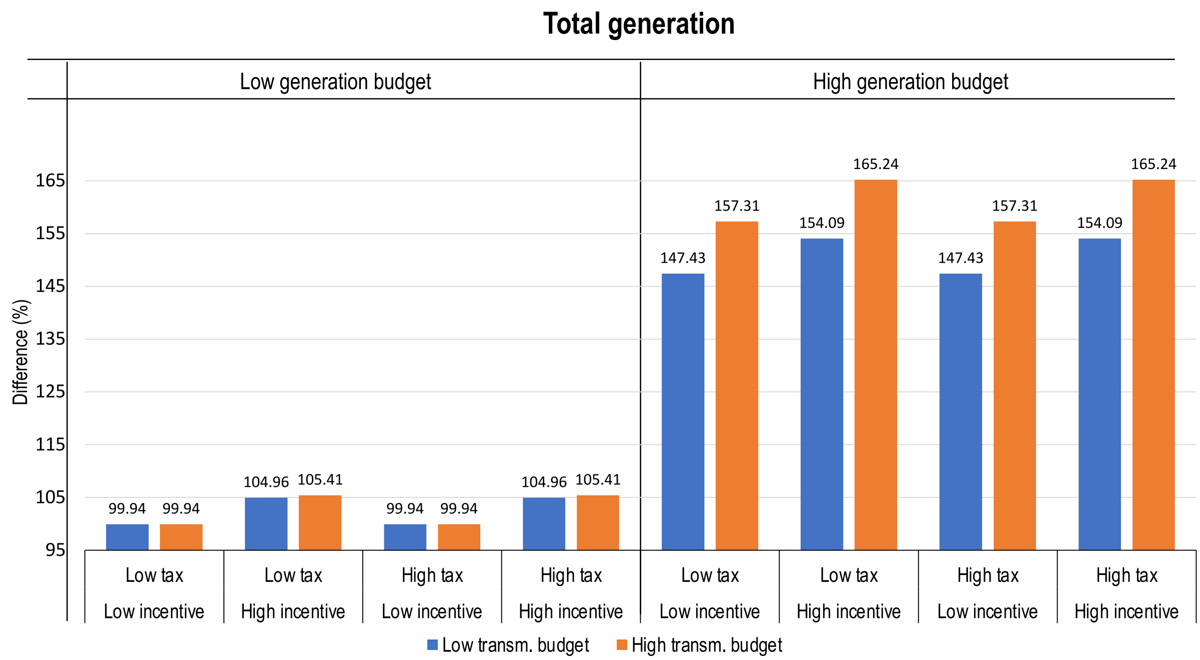

Fig. 19. Case study: Impact of transmission capacity expansion budget on total generation.

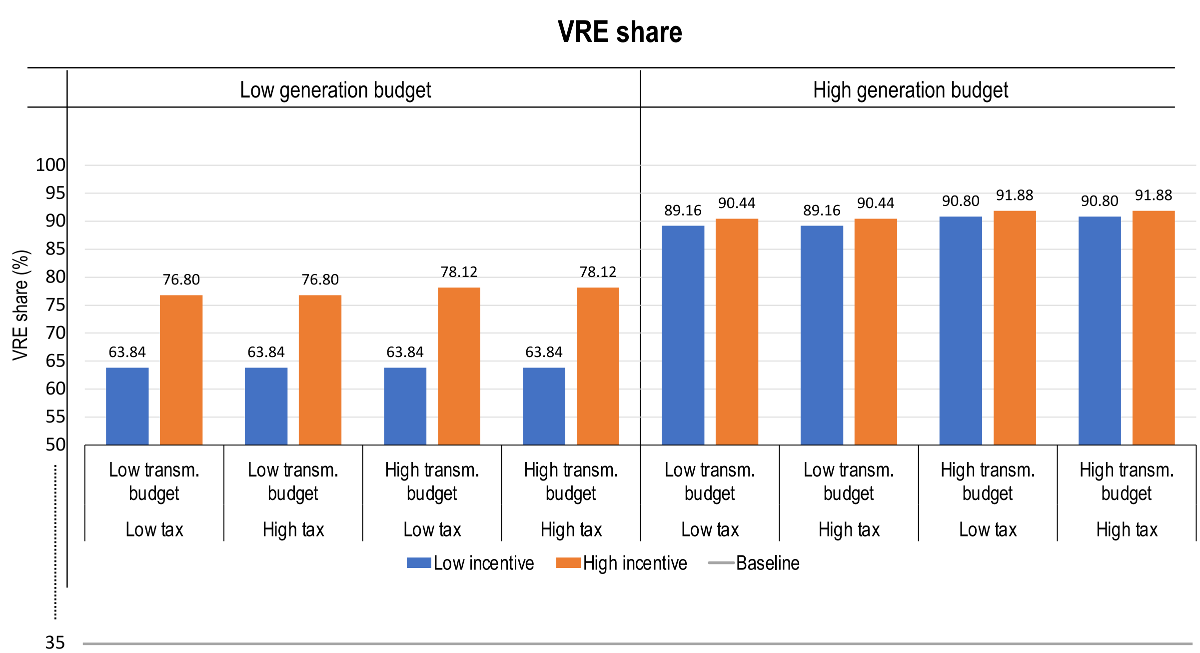

Fig. 20. Case study: Impact of VRE investment incentive on VRE share.

value between them. Following Schlachtberger et al. (2017), the length of the transmission lines we considered to be the distances between geographical midpoints of each country. In the case of the Baltic countries, the closest Baltic country to the corresponding Nordic country was used to represent the Baltic countries node. However, when calculating the distance between Sweden and the Baltic countries node, the distance between the mid-point of Sweden and the mid-point of Lithuania was considered due to the existing transmission capacity between these two countries. For the same reason, the distance between the mid-point of Finland and the mid-point of Estonia was considered to represent the transmission line between Finland and the Baltic countries.

The transmission expansion budget (TEB) values are based on the open data provided in the 2022 report of green solutions for Nordic energy system (Nordic TSOs, 2022). The report states that the investments in the transmission infrastructure planned over the next ten years exceed €25B. The project involves 4 TSOs: Fingrid (Finland), Energinet (Denmark), Statnett (Norway) and Svenska Kraftnät (Sweden). Hence, we assumed that a 10-year budget for one TSO would comprise €6.25B. The generation expansion budget (GEB) values are based on the Swedish GenCo VATTENFALL report (Vattenfall, 2022) indicating that the company planned growth investments of a total SEK 34 billion (about €3B) for 2022–2023. For the numerical experiments, the annual

Table 7
Primal variables.

Symbol	Description	Units
$g^e_{s,t,n,i}$	Conventional generation of the type $e \in E$ at the node $n \in N$ by producer $i \in I$ considering scenario $s \in S$ and time period $t \in T$	MWh
$g^r_{s,t,n,i}$	VRE generation of the type $r \in R$ at the node $n \in N$ from producer $i \in I$ considering scenario $s \in S$ and time period $t \in T$	MWh
$q_{s,t,n}$	Quantity of energy consumed at the node $n \in N$ considering scenario $s \in S$ during time period $t \in T$	MWh
$f_{s,t,n,m}$	Energy transferred from the node $n \in N$ to the node $m \in N$ considering scenario $s \in S$ and time period $t \in T$	MWh
$l^+_{n,m}$	Capacity added to the transmission line connecting nodes $n \in N$ and $m \in N$	MW
$\overline{g}^{e+}_{n,i}$	Generation capacity added to the conventional generation of the type $e \in E$ from the producer $i \in I$ at the node $n \in N$	MW
$\overline{g}^{r+}_{n,i}$	Generation capacity added to the VRE generation of the type $r \in R$ from the producer $i \in I$ at the node $n \in N$	MW

Table 8
Indices and sets.

Symbol	Description
$n \in N$	Nodes
$s \in S$	Availability scenarios
$e \in E$	Conventional energy sources
$r \in R$	Variable renewable energy sources
$i \in I$	Power producer companies
$t \in T$	Time periods

Table 9
Conventional generation parameters.

Symbol	Description	Units
$M^e_{n,i}$	Annualised maintenance cost for conventional generation of the type $e \in E$ from the producer $i \in I$ at the node $n \in N$	€/MW
$C^e_{n,i}$	Operational cost for conventional generation of the type $e \in E$ from producer $i \in I$ the node $n \in N$	€/MWh
$\overline{G}^e_{n,i}$	Installed generation capacity of the conventional generation of the type $e \in E$ from the producer $i \in I$ at the node $n \in N$	MW
$I^e_{n,i}$	Annualised capacity expansion investment cost for the conventional generation of the type $e \in E$ from the producer $i \in I$ at the node $n \in N$	€/MW
$R^{up,e}_{n,i}$	Maximum ramp-up rate for the conventional generation of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$	
$R^{down,e}_{n,i}$	Maximum ramp-down rate for the conventional generation of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$	
D^e	Carbon tax for conventional generation of the type $e \in E$	€/MWh

Table 10
VRE generation parameters.

Symbol	Description	Units
$M^r_{n,i}$	Annualised maintenance cost for VRE generation unit of the type $r \in R$ from the producer $i \in I$ at the node $n \in N$	€/MW
$\overline{G}^r_{n,i}$	Installed generation capacity of the VRE of the type $r \in R$ from the producer $i \in I$ at the node $n \in N$	MW
$I^r_{n,i}$	Annualised capacity expansion investment cost for the VRE of the type $r \in R$ from the producer $i \in I$ at the node $n \in N$	€/MW
$A^r_{s,t,n}$	Availability factor for VRE type $r \in R$ at the time period $t \in T$ considering scenario $s \in S$ at the node $n \in N$	

TEB and GEB values were levelled to a day-based scale by dividing them by 365. The data regarding the carbon tax is based on the data provided by the European review of energy taxation, carbon pricing and energy subsidies 2022 (European court of auditors, 2022). Following Energy for Growth Hub (2022), U.S. Environmental Protection Agency (2019), Partnership for policy integrity (2011) we assumed the amount of

Table 11
Dual variables.

Symbol	Description	Units
$\theta_{s,t,n}$	Shadow price on the power balance at node $n \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MWh
$\lambda^{f}_{s,t,n,m}$	Shadow price on the power flow primal feasibility constraint from the node $n \in N$ to the node $m \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MW
$\beta^{f_1}_{s,t,n,m}$	Shadow price on the transmission capacity for the power flow from the node $n \in N$ to the node $m \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MW
$\beta^{f_2}_{s,t,n,m}$	Shadow price on the transmission capacity for the power flow from the node $n \in N$ to the node $m \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MW
$\beta^{e}_{s,t,n,i}$	Shadow price on conventional energy capacity of the type $e \in E$ from the producer $i \in I$ at node $n \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MWh
$\beta^{r}_{s,t,n,i}$	Shadow price on VRE capacity of the type $r \in R$ from the producer $i \in I$ at node $n \in N$ considering scenario $s \in S$ during time period $t \in T$	€/MWh
$\beta^{up,e}_{s,t,n,i}$	Shadow price on the maximum ramp-up rate for the conventional generation of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$ considering scenario $s \in S$ during time period $t \in T$	
$\beta^{down,e}_{s,t,n,i}$	Shadow price on the maximum ramp-down rate for the conventional generation of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$ considering scenario $s \in S$ during time period $t \in T$	
$\lambda^{e+}_{n,i}$	Shadow price on non-negativity constraint for the conventional generation expansion of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$	
$\lambda^{r+}_{n,i}$	Shadow price on non-negativity constraint for the VRE generation expansion of the type $r \in R$ at the node $n \in N$ from the producer $i \in I$	
$\lambda^{e}_{s,t,n,i}$	Shadow price on non-negativity constraint for the conventional generation of the type $e \in E$ at the node $n \in N$ from the producer $i \in I$ considering scenario $s \in S$ during time period $t \in T$	
$\lambda^{r}_{s,t,n,i}$	Shadow price on non-negativity constraint for the VRE generation of the type $r \in R$ at the node $n \in N$ from the producer $i \in I$ considering scenario $s \in S$ during time period $t \in T$	
β^{g+}_{i}	Shadow price on upper-limit constraint for the generation expansion for the producer $i \in I$	

Table 12
Transmission parameters.

Symbol	Description	Units
$\overline{L}_{n,m}$	Installed capacity at the line connecting nodes $n \in N$ and $m \in N$	MW
$M^{l}_{n,m}$	Annualised maintenance cost for transmission per line connecting node $n \in N$ to the node $m \in N$	€/MW
$I^{l}_{n,m}$	Annualised capacity expansion investment cost for the line connecting node $n \in N$ to the node $m \in N$	€/MW
K^{L+}	Capacity expansion investment budget	€

emissions per MWh to be 0.50 tons of CO_2, 0.34 tons of CO_2, 0.99 tons of CO_2 and 0.23 tons of CO_2 for OCT, CCT, coal and biomass generation sources, respectively.

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