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DOI
10.1016/j.jup.2023.101707

Publication date
2024

Document Version
Final published version

Published in
Utilities Policy

Utilities Policy 87 (2024) 101707

Contents lists available at ScienceDirect

Utilities Policy

journal homepage: www.elsevier.com/locate/jup

Full-length article

Regulatory incentives for transmission system operators under flow-based market coupling

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ARTICLE INFO

Keywords:
Flow-based market coupling
Congestion management
Day-ahead markets
Incentive regulation

ABSTRACT

Flow-based market coupling is a critical element of the electricity market in Europe. Transmission System Operators determine the commercial transmission capacity that can be implicitly traded in a zonal day-ahead market. However, this entails a trade-off: higher commercial transmission capacities increase market efficiency, affecting the electricity market prices, but also increase redispatch costs, affecting the network tariff. The decision on the commercial transmission capacity should optimally balance day-ahead welfare and redispatch costs, but depends on the rules and regulated incentives enforced on the TSOs. A MinRAM criterion, i.e., imposing minima for the commercial transmission capacity, is a one-size-fits-all policy without variation in time and space that unlikely leads to optimal transmission capacity allocation and is hard to tune because regulators have incomplete information. Incentive regulation is an alternative policy instrument promoting welfare-maximizing commercial transmission capacities, robust against information asymmetry. We provide a set of mathematical conditions to properly design an incentive scheme that rewards price convergence and penalizes excessive redispatch costs. Therefore, this paper serves as a stepping stone towards tapping the full potential of cross-border trade in zonal markets for policymakers, regulators, TSOs and market participants.

1. Introduction

Interconnected power markets have been proven to be economically beneficial (European Commission, 2020). However, the zonal market design in Europe leads to a disconnect between commercial and physical power flows. Commercial exchange assumes point-to-point power flow from producer to consumer, while the physical power follows Kirchoff's laws, distributing power through a complex network of parallel transmission lines. A zonal market, having a uniform wholesale electricity price over an entire zone, does not fully capture the physical power flows in the transmission grid (Androcec et al., 2009). Therefore, to avoid excessive transmission line overloading, the commercial transmission capacity is lower than the physical transmission capacity (Schönheit et al., 2022). Fig. 1 shows the commercial cross-border transmission capacity w.r.t the physical capacity in 2021 in the Central-Western European countries as an illustration (ACER, 2022). During at least 95% of the hours in 2021, the commercial capacity does not exceed 70% of the physical capacity in Belgium, France and the Netherlands, and does not exceed 50% in Germany.

Transmission System Operators (TSOs) are entitled to determine the commercial transmission capacity that can be implicitly traded in the day-ahead market on an hourly basis, i.e., the (cross-border) capacity calculation (European Commission, 2015). In case the market outcome would violate physical grid constraints, TSOs perform corrective actions (e.g., redispatch) to ensure feasible power flows, implying a deviation of the generation schedule from the dispatch schedule determined through the market clearing (Weibelzahl, 2017). As a result, determining commercial transmission capacities is a multi-objective problem: higher transmission capacities increase the market efficiency (affecting the electricity market prices), but also increase the probability of redispatch costs (affecting the network tariff) (Schönheit et al., 2021).

Regulatory frameworks are necessary to incentivize welfare-optimal commercial transmission capacities. Glachant et al. (2013) state that network operators perform multiple tasks with different characteristics which poses a challenge to regulation. Moreover, Oggioni and Smeers (2013) argue that regulatory intervention in cross-border trade is necessary as TSOs might naturally restrict commercial transmission capacities to limit congestion management efforts. Regulators report that commercial cross-border transmission capacities are, in their

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https://doi.org/10.1016/j.jup.2023.101707
Received 26 May 2023; Received in revised form 29 December 2023; Accepted 29 December 2023
Available online 13 January 2024

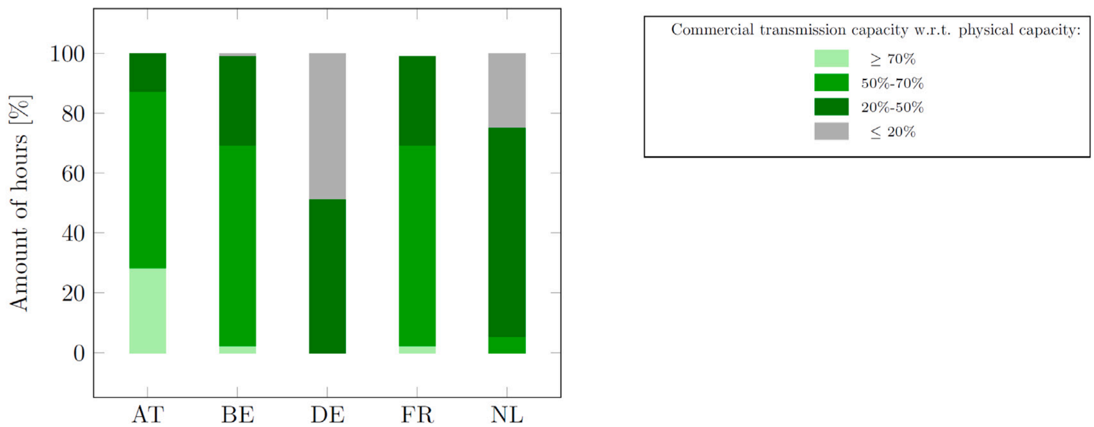


Fig. 1. Relative amount of time in 2021 where the commercial cross-border transmission capacity for trade reached a specified fraction of the physical transmission capacity (ACER, 2022).

opinion, too low (CREG, 2017). Therefore, current regulatory frameworks mainly consist of MinRAM criteria, i.e., imposing minimal fractions of the physical transmission capacity that should be made available to the market to stimulate cross-border trade. However, MinRAM criteria require regulators to possess information on the welfare-optimal commercial transmission capacities and, therefore, are prone to an erroneous determination of MinRAM criteria and, consequently, welfare losses (50Hertz et al., 2020).

Incentive regulation could overcome the issue of information asymmetry between regulators and TSOs (Joskow, 2008). However, research on the application of incentive regulation to cross-border trade is scarce, despite that it is used in practice (CREG, 2019), and that literature signals the need for an adequate regulatory framework (Glachant et al., 2013; Oggioni and Smeers, 2013). This paper fills this gap and answers how incentive regulation affects the welfare gain of cross-border electricity trade and whether the full potential of trade can be achieved by optimally designing the incentive. Specifically, the contribution of this paper is two-fold. First, we illustrate that, in the absence of incentive regulation, commercial transmission capacities and welfare, can vary substantially depending on a TSO's objectives and risk attitudes. Second, we show that incentive regulation is an essential tool for regulators to maximize the welfare gain from (cross-border) electricity trade. Specifically, we provide a set of mathematical conditions to properly design an incentive scheme that rewards market efficiency and penalizes excessive redispatch costs.

This paper is structured as follows. While Section 2 introduces the state-of-the-art in the scientific literature, Section 3 presents an analytical analysis of incentive regulation. Section 4 illustrates the welfare implications of (cross-border) trade with and without incentive regulation using a stylized power system. The numerical illustration aims to provide a complete understanding of the presented concepts, solving two optimization problems. Section 5 discusses the results and Section 6 concludes.

2. Related literature

There exist two methods for cross-border capacity allocation: Flow-Based Market Coupling (FBMC) and Available Transfer Capacity (ATC). FBMC is the target method in Europe and has been active in Central-Western Europe[1] since 2015 and in the CORE region[2] since 2022 (ACER, 2019; Vajdić and Kelava, 2020). The ATC method implies a static zone-to-zone description of the commercial cross-border transmission capacity. The FBMC method, on which this paper focuses, comes with a more accurate, though less rigorous than under a nodal market design, representation of grid constraints and also considers critical intra-zonal transmission lines (Kristiansen, 2020). Specifically, prior to the market clearing, TSOs determine a set of parameters that (i) allows the market operator to estimate the flows on selected critical network elements, e.g., zonal Power Transfer Distribution Factors (PTDFs), and (ii) determines the commercial transmission capacity to be implicitly traded in the day-ahead market, i.e. the limits on the estimated flows (Remaining Available Margin, RAM) (Van den Bergh et al., 2016). The flow-based parameters lead to a unique trading domain for each hour, i.e., the space of possible net exchange positions of the different market zones. We refer the reader to Schönheit et al. (2021) for an exhaustive guide on the flow-based parameters.

This paper focuses on FBMC rather than ATC because (i) FBMC allows for line-specific commercial transmission capacities, rewarded or penalized under an incentive scheme, which is not the case under ATC, (ii) most existing literature on FBMC suggests the need for proper regulation, and (iii) FBMC is the target methodology in the EU.

Fig. 2 shows the typical structure of models in literature on FBMC and in this paper (Schönheit et al., 2021; Lété and Papavasiliou, 2021; Weinhold and Mieth, 2021; Voswinkel et al., 2019). The FBMC method impacts three stages, represented by an optimization problem at each stage. First, two days before delivery (D-2), TSOs determine the flow-based parameters characterizing their expectation of the state of the grid on the day of delivery (D). These parameters, including the RAMs for each critical network element, serve as technical limitations in the day-ahead (DA) market clearing algorithm performed by the market operator one day before delivery (D-1), representing the second stage. However, since the limitations of the grid are only represented in the market to a limited extent, congestion might still appear in real time without intervention. Therefore, redispatch by the TSO might be necessary to ensure the safe operation of the transmission grid on the day of delivery (D) in the third stage. The TSO is affected in its actions by the regulatory framework, by the characteristics of the transmission grid and by the bids of the market participants.

In that context, a large part of the research on FBMC focuses on the flow-based parameters, showing that there exists wiggle room for the TSO to set the flow-based domains. Marien et al. (2013) show that these parameters impact the market equilibrium and prices, hence, impacting the efficiency of the market clearing. Wyrwoll et al. (2018) support this conclusion and add that the design of the parameters also impacts the generation mix. Investigating the parameter-specific impacts, Schönheit et al. (2020b) show that trading domains, i.e. the space of feasible net export positions of the market zones as a result of

[1] Central Western Europe consists of Austria, Belgium, France, Germany and the Netherlands.

[2] The CORE region comprises Austria, Belgium, Croatia, the Czech Republic, France, Germany, Hungary, Luxembourg, the Netherlands, Poland, Romania, Slovakia, and Slovenia.

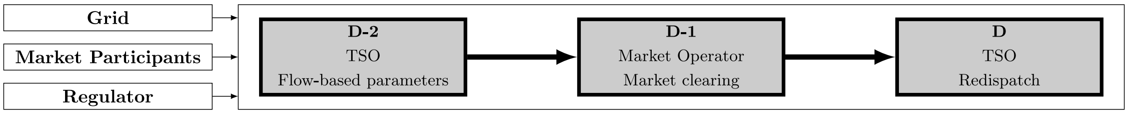


Fig. 2. Typical structure of models in literature on FBMC and in this paper: (i) determination of flow-based parameters in D-2 by TSOs, (ii) market clearing in D-1 by the market operator, and (iii) redispatch in D by the TSOs. The TSOs and market operator are affected in their actions by the regulator, the grid and the DA market participants. This paper focuses on the impact of the regulatory framework on the welfare gain of trade.

grid limitations, substantially vary in shape and size depending on the strategies that TSOs apply to determine the PTDFs. Moreover, literature exists in which one proposes novel strategies to determine the GSKs or other parameters. For example, Van den Bergh and Delarue (2016) propose an improved method to determine the PTDFs, while Schönheit et al. (2022) develop a novel method to determine the critical network elements. Finally, recent research focuses on the extension of the region in which the flow-based methodology is applied. While Bøet al. (2020) investigate the impact of the FBMC method in the Nordic region, Vajdić and Kelava (2020) focus on the CORE region.

TSOs are regulated monopolists in their zones (Meeus, 2020). They charge a transmission tariff to consumers. As an example of regulatory intervention, EU legislation imposes a minimal fraction of commercial transmission capacity, i.e. a minimal RAM (MinRAM) should be made available to the market to stimulate cross-border trade and, hence, price convergence. Specifically, a MinRAM of 20% (since 2018) and, more recently, 70% (starting 2025) of the physical transmission capacity should be available for trade (Council of the European Union and European Parliament, 2019). An increasing RAM corresponds to increasing day-ahead market welfare, allowing for more cross-border trade. However, it might also imply an increasing demand for redispatch actions that might counter the cost decrease resulting from a higher RAM (Matthes et al., 2019). Schönheit et al. (2020a) indeed report that a MinRAM criterion of 70% may lead to welfare losses because of the increasing redispatch costs that offset the gains in the day-ahead market clearing. Henneaux et al. (2021) report similar findings and advocate smart redispatch actions. A MinRAM criterion might not lead to the social optimum because it is a one-size-fits-all policy without variation in time and space. Moreover, it is hard to set the optimal criterion because regulators have incomplete information on the power system. Therefore, incentive regulation is an alternative policy instrument to incentivize welfare-maximizing commercial transmission capacities that is robust against information asymmetry and can be designed dynamically.

3. Incentive regulation

This section introduces a novel incentive regulation scheme based on a real-world case in Belgium (CREG, 2019) and the conditions for an optimal design of the parameters in the incentive regulation scheme. While we present incentive regulation in the context of FBMC, it could also be applied in the context of ATC. This is similar to MinRAM criteria, which fall under EU legislation and also apply to bidding zones that do not consider FBMC.

3.1. Definition

An incentive is a monetary reward or penalty for a TSO based on an ex-post evaluation by the regulating authority. We consider incentive I as the sum of two components, i.e., an ex-post evaluation of RAMs (J) and an ex-post evaluation of redispatch costs (K), which align with EU objectives (European Commission, 2020).

$$I = J + K \tag{1}$$

The first component aims to foster cross-border trade and price convergence among zones. Specifically, it evaluates the RAM of the transmission lines binding to the market clearing algorithm. A higher RAM implies a market clearing algorithm that is less restricted. We assume that the component in the incentive takes the following form, inspired by the Belgian regulator CREG (CREG, 2019):

$$J = \sum_{l \in \mathcal{L}} \frac{J_l \times \bar{J}}{|\mathcal{L}|} \tag{2}$$

with

$$J_l = \begin{cases} -1 & \text{if } RAM_l \in [0, -R^* + 2R^0] \\ \frac{RAM_l - R^0}{R^* - R^0} & \text{if } RAM_l \in [-R^* + 2R^0, R^*] \\ 1 & \text{if } RAM_l \in [R^*, 1] \end{cases} \tag{3}$$

with J_l a line-specific score for each binding transmission line $l \in \mathcal{L}$, with $|\mathcal{L}|$ the number of binding transmission lines, with RAM_l the RAM on a binding line l and with R^0, R^* and $\bar{J}$ as design parameters. If RAM_l is higher than a baseline R^0, a positive score J_l for line l is appointed. The line-specific score J_l cannot be higher than 1 or lower than −1 and reaches its maximum of 1 when $RAM_l \geq R^*$. The maximal reward or penalty based on this component in the incentive amounts to $\bar{J}$. We assume that RAM_l, R^0 and R^* are expressed relative to the physical transmission capacity of the considered transmission line, ranging from 0 to 1.

The second component aims to maintain the TSO tariff at acceptable levels and to foster a reliable transmission grid operation. As a proxy, it evaluates the redispatch cost that a TSO incurs while correcting the market outcome to ensure feasible power flows. We assume that the component in the incentive takes the following form.

$$K = -\alpha \times (RC - RC^0) \tag{4}$$

with RC the redispatch cost and α and RC^0 as design parameters. For each euro of redispatch cost above the baseline redispatch cost RC^0, a penalty of α is added to the incentive. The reverse is also true if $RC < RC^0$.

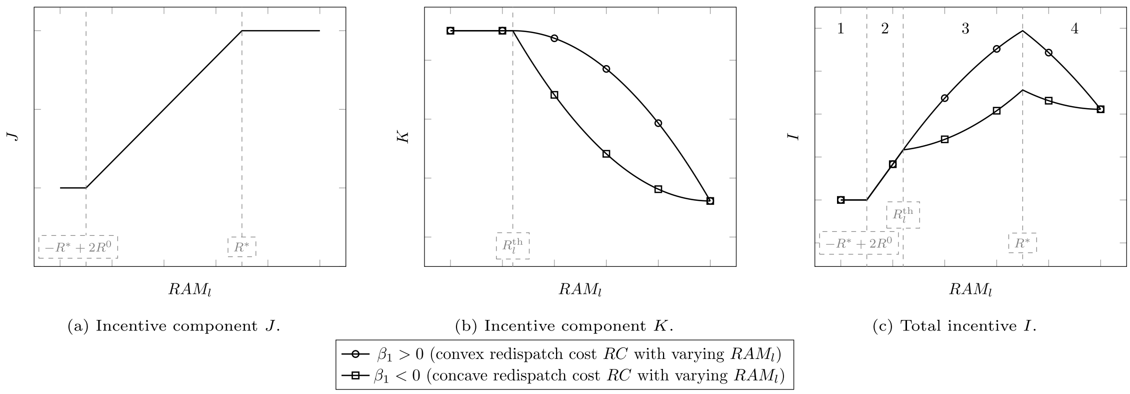
While J is only dependent on RAM_l for each $l \in \mathcal{L}$, K is dependent on RC, which varies with RAM_l for each $l \in \mathcal{L}$. In the remainder of this paper, we assume that $|\mathcal{L}| = 1$ for the sake of simplicity. Besides, we assume that the relation between RC and RAM_l takes the following form.

$$RC = \begin{cases} 0 & \text{if } RAM_l \in [0, R_l^{\text{th}}] \\ \beta_1 RAM_l^2 + \beta_2 RAM_l + \beta_3 & \text{if } RAM_l \in [R_l^{\text{th}}, 1] \end{cases} \tag{5}$$

with R_l^{th} a threshold below which RAM_l leads to a redispatch cost RC of zero as a sufficiently low commercial transmission capacity does not lead to transmission line overloading, hence, redispatch. R_l^{th}, β_1, β_2 and β_3 are parameters of the power system. We observe ex-post in Section 4 that this pattern accurately describes RC when RAM_l varies and we perform a polynomial regression to obtain β_1, β_2 and β_3.

Eq. (6) provides the incentive I when combining (1) to (5). It is a piece-wise function[3] with RAM_l as the only variable for the TSO. Fig. 3 visualizes a typical pattern of components J (Fig. 3(a)) and

[3] We assume that $R_l^{\text{th}} \in [-R^* + 2R^0, R^*]$ so that $J_l \in]-1, 1[$ at R_lth, which is reasonable as the welfare-optimal RAM_l typically leads to a non-zero redispatch cost.



(a) Incentive component J. (b) Incentive component K. (c) Total incentive I.

Fig. 3. A typical pattern of components J (panel a) and K (panel b) as well as the total incentive I (panel c) when RAM_l varies. We make a distinction between power systems with redispatch costs RC that increase convexly with RAM_l, implying that $\beta_1 > 0$, and power systems with redispatch costs RC that increase concavely with RAM_l, implying that $\beta_1 < 0$,.

K (Fig. 3(b)) as well as the total incentive I (Fig. 3(c)) when RAM_l varies. We make a distinction between power systems with redispatch costs RC that are convex in RAM_l, implying that $\beta_1 > 0$, and power systems with redispatch costs RC that are concave in RAM_l, implying that $\beta_1 < 0$, because the optimal design parameters of the incentive regulation scheme differ between both cases.

$$I = \begin{cases} -\bar{J} + \alpha \times RC^0 & \text{if } RAM_l \in [0, -R^* + 2R^0] \\ \frac{RAM_l - R^0}{R^* - R^0} \times \bar{J} + \alpha \times RC^0 & \text{if } RAM_l \in [-R^* + 2R^0, R_l^{\text{th}}] \\ \frac{RAM_l - R^0}{R^* - R^0} \times \bar{J} - \alpha & \\ \quad \times (\beta_1 \times RAM_l^2 + \beta_2 \times RAM_l + \beta_3 - RC^0) & \text{if } RAM_l \in [R_l^{\text{th}}, R^*] \\ \bar{J} - \alpha \times (\beta_1 \times RAM_l^2 & \\ \quad + \beta_2 \times RAM_l + \beta_3 - RC^0) & \text{if } RAM_l \in [R^*, 1] \end{cases} \tag{6}$$

3.2. Optimal design

An optimal choice of the parameters R^0, R^*, $\bar{J}$, α and RC^0 incentivizes a welfare-maximizing outcome w.r.t. trade of electricity, or equivalently, a system cost-minimizing outcome. The system cost consists of the cost of generation, based on the DA market's outcome, and the redispatch cost. An optimal design of incentive regulation implies the incentive is maximal when the commercial transmission capacity leads to the lowest system cost. We annotate the optimal transmission capacity of a line $l \in \mathcal{L}$ as RAM_l^{opt}, and for now assume it is a known parameter from the power system. We explain in Section 5 that incentive regulation, as opposed to MinRAM criteria, is also effective when RAM_l^{opt} is not known.

The piece-wise expression for I (see (6)) consists of four segments for four intervals of RAM_l. While the first segment is constant with changing RAM_l, the second segment is linearly increasing with increasing RAM_l regardless of the design parameters. The third and fourth segments are both quadratically dependent on RAM_l. This results implies that the maximum of I is found in the third or fourth segment ($RAM_l \geq R^{th}$), i.e., when I is a second-degree polynomial in function of RAM_l. Therefore, an optimal design of the parameters imposes that I is increasing with RAM_l in the third segment (a positive first-order derivative) and decreasing in the fourth segment (a negative first-order derivative) so that the maximum occurs at the boundary between the third and fourth segment where $RAM_l = R^*$.

Specifically, if RC is a concave function of RAM_l, i.e., $\beta_1 < 0$, the mathematical conditions take the following form.[4]

$$\frac{\delta I}{\delta RAM_l}\Big|_{RAM_l = R_l^{\text{th}+}} > 0 \tag{7a}$$

$$\frac{\delta I}{\delta RAM_l}\Big|_{RAM_l = 1} < 0 \tag{7b}$$

$$R^* = RAM_l^{\text{opt}} \tag{7c}$$

Using the definition of I in (6), (7) can be simplified as:

$$-2 \times \alpha \times \beta_1 \times R_l^{\text{th}} - \alpha \times \beta_2 + \frac{\bar{J}}{R^* - R^0} > 0 \tag{8a}$$

$$-2 \times \alpha \times \beta_1 - \alpha \times \beta_2 < 0 \tag{8b}$$

$$R^* = RAM_l^{\text{opt}} \tag{8c}$$

Note that (8b) depends entirely on the power system and might not be satisfied. If (8b) does not hold, I does not monotonously decrease with increasing RAM_l in the fourth segment. Hence, there is no guarantee that the incentive I is maximal at $RAM_l = RAM_l^{\text{opt}}$. However, it is reasonable to assume that (8b), implying that $\beta_2 > -2 \times \beta_1$, is satisfied for typical regressions of RC with varying RAM_l.

If RC is a convex function of RAM_l, i.e., $\beta_1 > 0$, the mathematical conditions take the following form.

$$\frac{\delta I}{\delta RAM_l}\Big|_{RAM_l = R^{*-}} > 0 \tag{9a}$$

$$\frac{\delta I}{\delta RAM_l}\Big|_{RAM_l = R^{*+}} < 0 \tag{9b}$$

$$R^* = RAM_l^{\text{opt}} \tag{9c}$$

Using the definition of I in (6), (9) can be simplified as:

$$-2 \times \alpha \times \beta_1 \times R_l^* - \alpha \times \beta_2 + \frac{\bar{J}}{R^* - R^0} > 0 \tag{10a}$$

$$-2 \times \alpha \times \beta_1 \times R_l^* - \alpha \times \beta_2 < 0 \tag{10b}$$

$$R^* = RAM_l^{\text{opt}} \tag{10c}$$

Similarly, as before, (10b) depends entirely on the power system. If it does not hold, I does not monotonously decrease with increasing RAM_l in the fourth segment. However, it is reasonable to assume that (10b) is satisfied for typical regressions (β_2 is typically positive) of RC with varying RAM_l.

[4] Note that an upper script at the evaluation point of the derivative of '+' (for the right-hand derivative) or '-' (for the left-hand derivative) specifies the derivative at a discontinuity in I.

The convex character of RC also allows for designing the incentive I in another way. Specifically, we can impose that a maximum occurs in the third segment of I (first order condition) while I monotonously decreases with RAM_l in the fourth segment. The mathematical conditions read as follows.

$$\frac{\delta I}{\delta RAM_l}|_{RAM_l=RAM_l^{opt}} = 0 \tag{11a}$$

$$\frac{\delta I}{\delta RAM_l}|_{RAM_l=R^{*+}} < 0 \tag{11b}$$

Using the definition of I in (6), (11) can be simplified as:

$$-2\times\alpha\times\beta_1\times RAM_l^{opt} - \alpha\times\beta_2 + \frac{\bar{J}}{R^* - R^0} = 0 \tag{12a}$$

$$-2\times\alpha\times\beta_1\times R_l^* - \alpha\times\beta_2 < 0 \tag{12b}$$

In conclusion, the structure of this incentive regulation scheme allows regulators to choose parameters R^0, R^*, $\bar{J}$, α and RC^0 so that the incentive peaks at RAM_l^{opt} at which the system cost is minimized. In case the regulator does not know $RAM_l^{opt}, \beta_1, \beta_2$ or β_3, i.e., the parameters that depend on the power system, the relation between the given incentive I and the observed TSOs' actions allows regulators to obtain information on these parameters ($RAM_l^{opt}, \beta_1, \beta_2$ and β_3) as Section 5 discusses. This approach contrasts with minRAM criteria, with which regulators cannot obtain information on the power system based on the TSOs' actions.

4. Numerical illustration

We consider a stylized power system for the sake of simplicity. First, we show that, without incentive regulation, RAMs and system costs can vary widely depending on the TSO's objectives and risk attitudes. Second, we show that adequate incentive regulation can guarantee a system cost-minimal outcome.

4.1. Data

We present two illustrative examples by application of the market clearing model and redispatch model from Schönheit et al. (2021) on two variations (Case A and Case B) of the 4-node/3-zone stylized network from Aravena (2018). The conditions in this paper are easily scalable to large-scale power networks by introducing a new set of conditions ((7), (9) or (11)) for each additional binding transmission line. However, it would bring visualization challenges while the concepts and insights presented in this paper would remain unchanged. Specifically, $|\mathcal{L}|$ binding transmission lines imply an $|\mathcal{L}|$-dimensional vector to represent the optimal values for RAM_l leading to an $|\mathcal{L}+1|$-dimensional visualization of the system cost SC with changing RAMs. Therefore, a stylized power system suffices to show (i) the need for regulation in flow-based market coupling and (ii) that incentive regulation can outperform currently existing policy instruments. The models are two sequential optimization problems: the market clearing minimizes generation costs considering an inelastic demand, and the redispatch model minimizes redispatch costs. In these models, we ignore technical tools from TSOs to operate the grid, such as phase-shifting transformers, dynamic line rating or transmission switching, and take the (possible sub-optimal) grid topology, market design and bidding zone configuration as given. The stylized network serves as an input to both models, and the generation dispatch from the market clearing model also is an input to the redispatch model. The stylized network has only one binding transmission line $l \in \mathcal{L}$, and we vary RAM_l from 0 up to 1 (expressed relative to the physical transmission capacity). We consider uncertainty on the generators' quantity bids in the day-ahead market with a set of scenarios. Therefore, we run the models for each RAM_l and scenario. Each scenario comes with a given probability. As a result, we obtain the cost in all scenarios with varying RAM_l and use this as a starting point for the numerical illustration. Fig. 4 visualizes the computational procedure. Case A entails a power system in which the redispatch cost RC increases convexly with increasing RAM_l, while Case B entails a power system in which RC increases concavely with RAM_l. Appendix provides more details on the set-up of the numerical illustration.

Table 1
Characteristics of the power system under Case A and Case B.

	Case A	Case B
R_l^{th} [%]	24	24
RAM_l^{opt} [%]	64	24
β_1 [-]	0.2343	−0.5303
β_2 [-]	7.2641	131.36
β_3 [-]	36.395	−2991.5

Fig. 5 shows the system cost SC with varying RAM_l, i.e., the commercial transmission capacity. The system cost SC is the sum[5] of the operational cost of generation, based on the DA market outcome, and the redispatch cost RC. Specifically, Fig. 5 shows, for both Case A and Case B, the expected and median value and the 5%–95% and 25%–75% percentile intervals. We obtain the expected cost as a weighted sum of the costs in each scenario with the related probabilities as weights. Note that the borders of the percentile intervals might overlap because the costs in some scenarios are identical. The dots highlight the RAM-cost pairs that we will discuss. The pattern of the expected total cost with varying RAM_l follows what is described in the literature (Schönheit et al., 2021, 2020a; Matthes et al., 2019; Henneaux et al., 2021).

Table 1 presents the characteristics of the power system under Case A and Case B. R_l^{th}, i.e., the threshold below which RAM_l leads to an expected redispatch cost $E[RC]$ of zero, is 24% for both cases. Fig. 5 shows that RAM_l^{opt} amounts to 64% under Case A and 24% under Case B which leads to the welfare-maximizing outcome of the day-ahead market and redispatch actions. A polynomial regression,[6] from which we derive the fitted coefficients β_1, β_2 and β_3, indicates that $E[RC]$ closely follows a second-order polynomial when $RAM_l \geq R_l^{th}$.

4.2. Without incentive regulation

In the absence of incentive regulation, a TSO might deviate from the welfare-optimal decision on RAM_l due to, among others, the uncertainty at hand, budget constraints or incomplete information (Oggioni and Smeers, 2013). We consider three strategies to determine RAM_l: (i) risk-neutral minimization of SC, i.e., acting as a social planner, (ii) risk-averse minimization of SC, and (iii) minimization of the redispatch cost. Additionally, we impose three variations of a MinRAM criterion (0%, 40% and 70%) as a constraint to each strategy. We "manually" determine the optimal RAM_l (and related system cost SC) for the different objectives and risk attitudes by graphically analyzing Fig. 5.

Table 2 presents the outcomes, i.e., a decision[7] on RAM_l leading to a value for $E[SC]$, of each strategy with three variations of a MinRAM criterion under Case A and Case B by referring to the unique outcomes that Fig. 5 presents. The red dot refers to the system cost-minimizing, or equivalently, the welfare-maximizing outcome. We observe variation in $E[SC]$ depending on the strategy. Specifically, we identify three potential sources for welfare losses when determining RAM_l: (i) risk aversion, (ii) prioritizing redispatch costs, incurred by the TSO, over the system cost, and (iii) a MinRAM criterion.

[5] Note that the costs arise from a purely fictive power system and, hence, their absolute values should not be interpreted further.

[6] The R-squared values from the regressions using a least squares method are 0.999 and 1.000, which indicates that nearly all variation in the expected redispatch cost can be declared by the regression.

[7] If multiple values for RAM_l are optimal under a specific objective, we assume that the highest optimal RAM_l is taken.

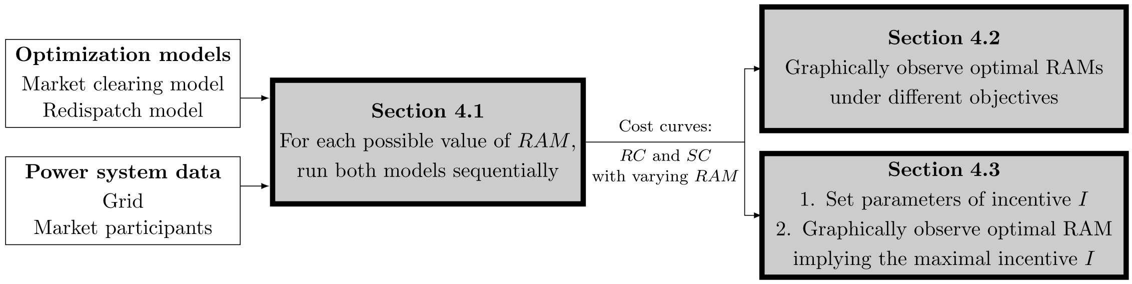


Fig. 4. Computational procedure leading to the presented results.

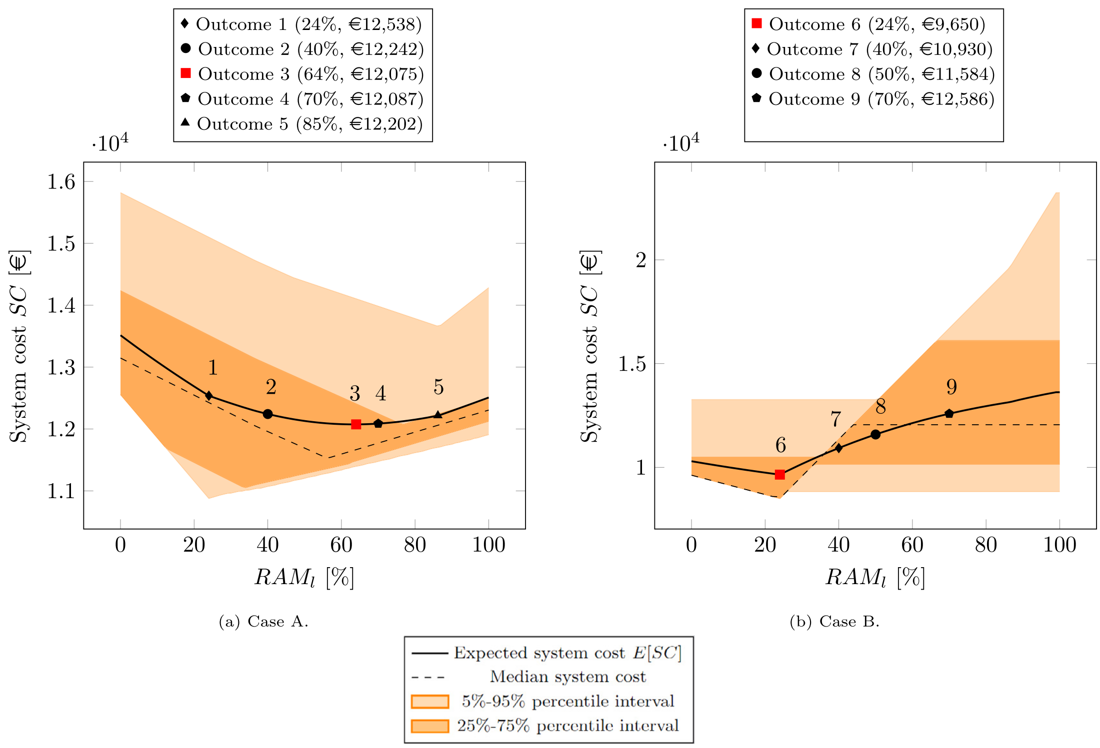


Fig. 5. System cost SC with varying RAM_l, i.e., the commercial transmission capacity. The expected and median value and the 5%–95% and 25%–75% percentile intervals are shown for both Case A and Case B. The dots highlight the RAM-cost pairs that we discuss.

Table 2
Outcome of each strategy with three variations of a MinRAM criterion under Case A and Case B. The numbers refer to the unique outcomes in Fig. 4.

	MinRAM		
	0%	40%	70%
Risk-neutral minimization of SC	3	3	4
Risk-averse minimization of SC	5	5	5
Minimization of the redispatch cost	1	2	4

(a) Case A. Outcome 3 is the optimal outcome.

	MinRAM		
	0%	40%	70%
Risk-neutral minimization of SC	6	7	9
Risk-averse minimization of SC	8	8	9
Minimization of the redispatch cost	6	7	9

(b) Case B. Outcome 6 is the optimal outcome.

First, minimization of SC with a risk averse attitude leads to a higher RAM_l and a higher $E[SC]$ than under RAM_l^{opt} in our numerical example.[8] Thus, despite more trade and, hence, price convergence than under the optimal outcome, the decrease in the expected cost of generation from the day-ahead market is overcompensated by an increase in the expected redispatch cost. This finding holds for both Case A and Case B where the increase in $E[SC]$ (outcomes 5 and 8) compared to the minimal expected cost (outcomes 3 and 6) amounts to 1% and 20%, respectively.

Second, prioritizing the redispatch cost over SC, or equivalently, avoiding redispatch actions, increases $E[SC]$ by 4% for Case A (outcome 1) but does not affect RAM_l nor $E[SC]$ for Case B (outcome 6) compared to the minimal expected system cost (outcome 3 and outcome 6). A minimal redispatch cost could imply a more restricted

[8] We assume that, under risk aversion, the TSO optimizes the scenario that aligns with the 95% quantile, meaning that the probability is 95% that the realized system cost will ex-post be lower than the system cost in this scenario. Compared to the redispatch cost, the day-ahead generation cost is higher under this pessimistic scenario than the expected scenario, shifting the minimum to the right, i.e., at $RAM_l > RAM_l^{opt}$.

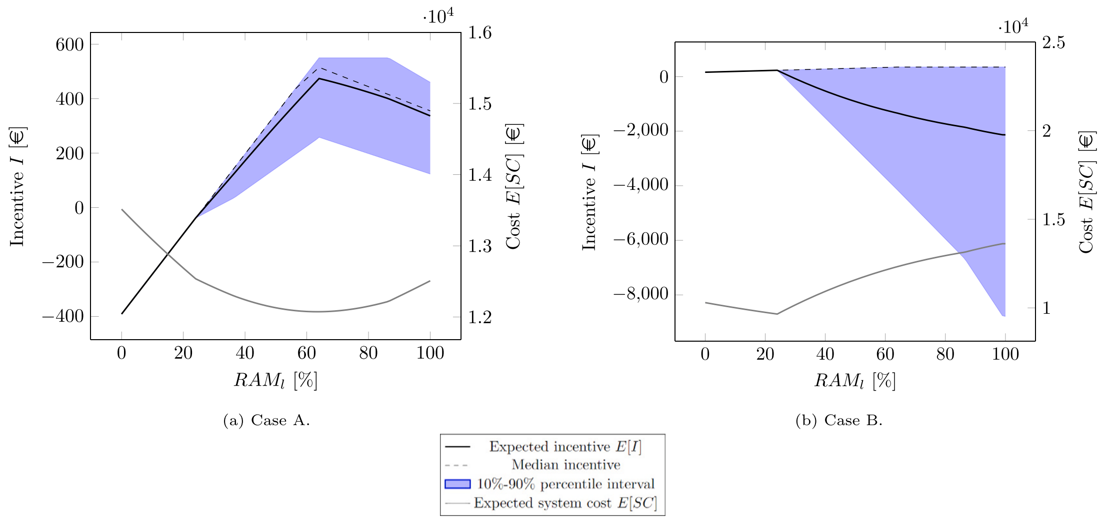


Fig. 6. Optimal incentive I (left axis) with varying RAM_l, i.e., the commercial transmission capacity. The expected and median values and the 10%–90% percentile interval are shown for both Case A and Case B. The expected system cost $E[SC]$ (right axis) is also shown.

market and, hence, a higher cost of generation from the day-ahead market than what is welfare-optimal.

Third, a MinRAM criterion can lead to welfare losses. Even in the case of a risk-neutral minimization of SC, a 70% MinRAM criterion imposes that RAM_l amounts to 70% which exceeds RAM_l^{opt} for both Case A and Case B. This increases $E[SC]$ by 0.1% (outcome 4) in Case A and by 30% (outcome 9) in Case B compared to the minimal expected system cost (outcome 3 and outcome 6). Nevertheless, MinRAM criteria could be a welfare-increasing measure in particular cases. For example, if the TSO follows a strategy that minimizes the expected redispatch cost, a 40% MinRAM criterion decreases $E[SC]$ by 2% in Case A (outcome 2) compared to when no MinRAM criterion is active (outcome 1).

4.3. With incentive regulation

We assume a TSO maximizes the expected incentive $E[I]$ when determining RAM_l. Table 3(a) and Table 3(b) present possible combinations of parameters for incentive regulation for Case A and Case B. The parameters are optimal[9] because they satisfy (8) and (10).

We analytically construct I for each possible RAM_l and scenario (and hence, RC) using Eq. (6). Fig. 6 shows I (left axis) with varying RAM_l, i.e., the commercial transmission capacity. The expected and median values and the 10%–90% percentile intervals are shown for both Case A (design parameters in Table 3(a)) and Case B (design parameters in Table 3(b)). $E[SC]$ (right axis) is also shown. We graphically observe that the maximum in $E[I]$ aligns with the minimum in $E[SC]$ under both Case A at RAM_l^{opt} = 64% and under Case B at RAM_l^{opt} = 24%.

In case the design parameters do not satisfy the conditions, the maximum in $E[I]$ implies a suboptimal $RAM_l \neq RAM_l^{opt}$. For example, in case the incentive design in Table 3(a), which is optimal for the power system in Case A, applies to the power system in Case B, $E[SC]$ increases by 28% (from €9,650 to €12,325) compared to the minimal $E[SC]$ under Case B. Specifically, the maximum of $E[I]$ occurs at RAM_l = 64% in that case instead of at RAM_l^{opt} = 24%. Thus, the incentive component J, rewarding higher RAMs, is too large, and the incentive component K, penalizing an excessive redispatch cost, is too small. Contrary, in case the incentive design in Table 3(b), which is optimal for the power system in Case B, applies to the power system in Case A, $E[SC]$ increases with 3.8% (from €12,075 to €12,537) compared to the minimal $E[SC]$ under Case A.

Uncertainty on the incentive I exists due to uncertainty on the redispatch cost RC and is captured in scenarios. In this numerical illustration, maximizing I in a pessimistic scenario, e.g., the 10%-percentile where $I < E[I]$, still leads to RAM_l^{opt}. However, this cannot be generalized because the imposed conditions assume risk neutrality in maximizing I because β_1, β_2 and β_3 are the fitted coefficients of $E[RC]$. Additional conditions are necessary to make the incentive regulation scheme robust against risk aversion. Specifically, the same conditions as laid out in Section 3 should hold, but with β_1, β_2 and β_3 representing the fitted coefficients of RC with changing RAM_l in a pessimistic scenario instead of the expected scenario ($E[RC]$).

Finally, multiple degrees of freedom exist to design an optimal incentive for a specific power system. Specifically for our numerical example, there are five design parameters, more than the necessary conditions for an optimal design (3). Therefore, there exist, among others, options to shift the expected incentive curve along the y-axis, impacting the magnitude of I. Alternatively, the peak in the incentive could be made more flat through a lower value for α to, e.g., limit the welfare loss in case the regulator has imperfect information on the power system.

5. Discussion

Regulators and policymakers should (i) recognize the possible deviation of TSOs from a social planner's behavior and (ii) take actions to stimulate welfare-optimal outcomes of the day-ahead market and redispatch actions. Two options, among others, are MinRAM criteria and incentive regulation. MinRAM criteria are a rigorous way to enforce more price convergence. However, such a criterion should be based on a techno-economical analysis to stimulate a welfare-optimal determination of RAMs. If MinRAM criteria are not adequately designed, suboptimal outcomes will be reached. Therefore, it is unlikely that a static (i.e., time and space-independent) minRAM criterion will yield welfare-maximizing outcomes.

Monetary incentives could help overcome an imperfect setting as these allow regulators to recognize the multiple objectives under cross-border trade: wholesale market efficiency and a reliable electricity grid operation. A careful design of the incentive is necessary as the incentive

[9] Note that an infinite number of combinations of parameters exists that are optimal.

Table 3
Optimal parameters for incentive regulation under Case A and Case B following (10) and (8) respectively.

Incentive component J		Incentive component K	
R^0	30%	α	0.1
R^*	64%	RC^0	€500
$\bar{J}$	€500		

(a) Case A following (10).

Incentive component J		Incentive component K	
R^0	10%	α	0.5
R^*	24%	RC^0	€500
$\bar{J}$	€100		

(b) Case B following (8).

components, each serving its own objective, are counteracting. A well-thought-out trade-off, presented in a mathematical form in Section 3, results in the welfare-optimal outcome.

In reality, it might be that initial objectives (e.g., minimization of redispatch costs) are part of the TSOs' objective in addition to the incentive regulation scheme. In that case, the optimized RAMs would lay in between the RAM under the initial objective and the welfare-optimal RAM. Here, we assume the TSO solely focuses on incentive I for illustrative purposes.

Designing an optimal incentive requires information on the costs of power trade under different RAMs. Specifically, the methodology in our paper requires information on the redispatch cost with varying RAM (to estimate β_1, β_2 and β_3 statistically) as well as on the RAM that leads to the minimal expected system cost, i.e., RAM_l^{opt}. The complexity of real-world power systems and possible information asymmetry between regulators and TSOs might not allow regulators to have information on these parameters. If this information were available, regulators could simply oblige the optimal RAM, leading to a first-best solution without additional regulatory intervention. Without information on these parameters, incentive regulation allows for a second-best solution in which the relation between the given incentive and the observed TSOs' actions allows regulators to obtain information on the costs under different RAMs. If the observed RAM differs from the RAM at which the regulator expects the incentive to be maximal, the TSO signals that the regulator's estimation of the costs with varying RAM is imperfect. Specifically, if the observed RAM is lower than expected by the regulator, the redispatch costs compared to the day-ahead generation costs are higher than estimated when designing the incentive, and vice versa. This information allows the regulator to gain information on the redispatch cost with varying RAM, i.e., β_1, β_2 and β_3, as well as on RAM_l^{opt} such that the future incentive is relatively more accurate. Overcoming the issue of information asymmetry comes with implementation challenges as the data set with historical incentives and related observed RAMs needs to be sufficiently large for an accurate estimation of the costs.

Finally, our paper takes the bidding zone configuration as given. Thus, we accept that loop flows are present following the methodology of FBMC, leading to a trade-off when setting RAMs between market efficiency and redispatch costs. Subsequently, we aim to optimize the outcome for the system as a whole when proposing incentive regulation. This approach should, however, not prevent stakeholders from addressing structural congestion through a bidding zone reconfiguration or grid reinforcements as outlined in the EU's Clean Energy Package (Council of the European Union and European Parliament, 2019).

6. Conclusion

Flow-based market coupling is prone to cost-efficiency losses as TSOs determine the commercial transmission capacity. The welfare-maximizing commercial transmission capacity involves a careful trade-off between day-ahead generation costs and redispatch costs. However, without regulatory intervention, commercial transmission capacities and welfare can greatly vary depending on a TSO's objectives and risk attitudes. MinRAM criteria, i.e., imposing minima for the commercial transmission capacity, is a one-size-fits-all policy without variation in time and space that unlikely leads to optimal transmission capacity allocation because it risks excessive redispatch costs by a priori reducing the space of possible commercial transmission capacities. Moreover, MinRAM criteria require regulators to possess information on the welfare-optimal commercial transmission capacities and, therefore, are prone to welfare losses.

Well-designed incentive regulation approximates the welfare-optimal outcome, under given and possibly sub-optimal grid topology, market design and bidding zone configuration, as it considers multiple objectives of cross-border trade: the market efficiency and the power grid reliability. Moreover, it can overcome the issue of information asymmetry between TSOs and regulators and, therefore, can outperform MinRAM criteria. Specifically, we provide mathematical conditions to properly design an incentive scheme that rewards price convergence and penalizes excessive redispatch costs. As a result, this paper serves as a first step for policymakers, regulators, TSOs and market participants to tap the full potential of cross-border trade.

CRediT authorship contribution statement

Michiel Kenis: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kenneth Bruninx:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Erik Delarue:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

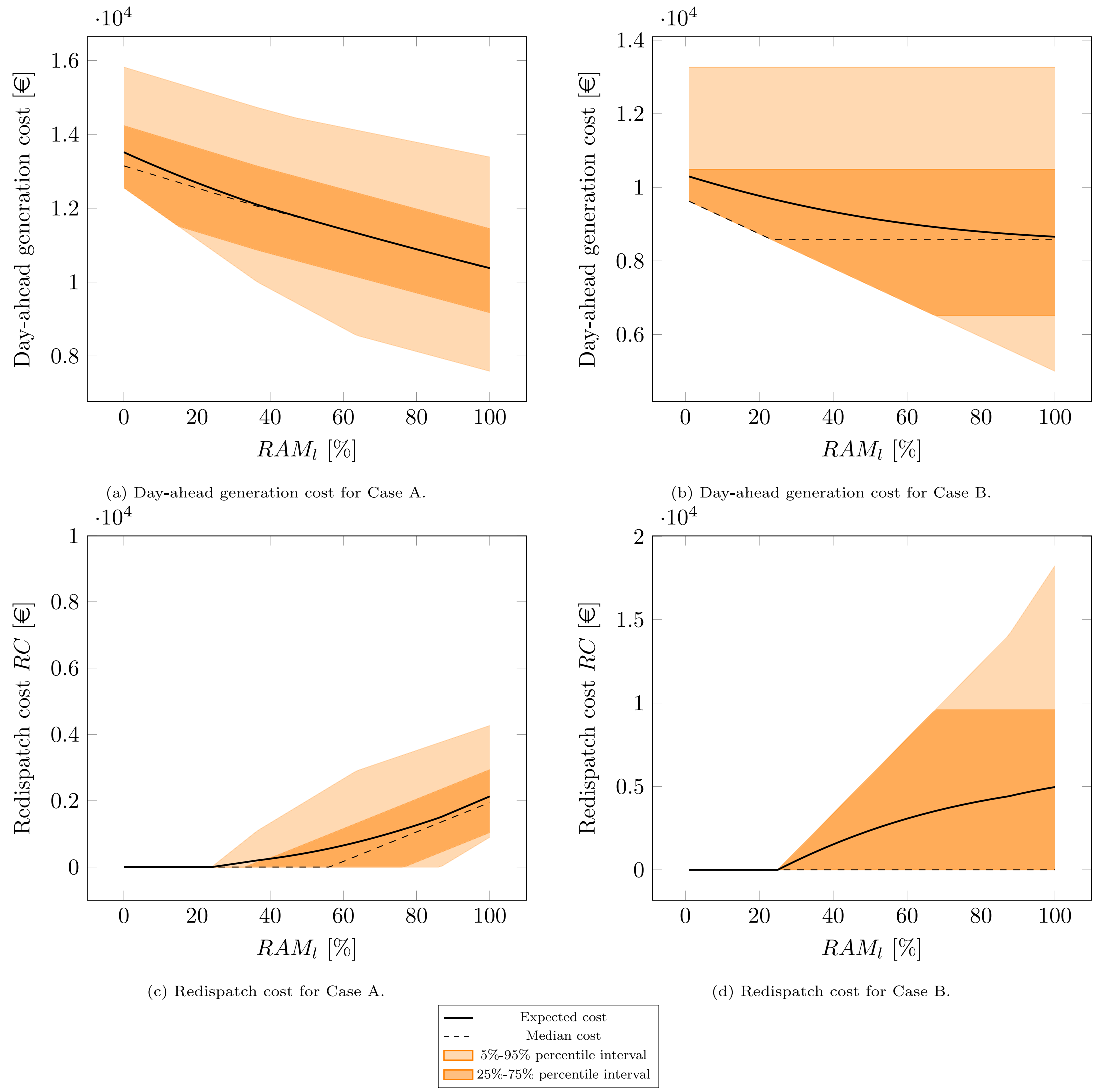
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix. Set-up of numerical illustration

We use the 4-node/3-zone stylized network from Aravena (2018). Table 4 shows the generation capacity and marginal cost of the generator at each node. The generator at node 1 represents an intermittent renewable energy source. Demand amounts to 300 MW at both node 2 and node 4. All transmission lines have an unlimited capacity, except line l_{41}, which has a capacity of 100 MW. An uncertain load factor of the renewable generation capacity at node 1 characterizes the scenarios to be considered to capture possible market clearing and redispatch outcomes. Specifically, the load factor follows a normal distribution with an average of 0.5 and a standard deviation of 0.165. This results in a set $\mathcal{S}$ with 100 scenarios s for generation at node 1. Fig. 7 shows the day-ahead generation cost and redispatch cost RC with varying RAM_l, i.e., the commercial transmission capacity, on line l_{41}. The expected and median values as well as the 5%–95% and 25%–75% percentile intervals are shown for both case A and case B.



(a) Day-ahead generation cost for Case A.
(b) Day-ahead generation cost for Case B.
(c) Redispatch cost for Case A.
(d) Redispatch cost for Case B.

Fig. 7. Day-ahead generation cost and redispatch cost RC with varying RAM_l, i.e., the commercial transmission capacity. The expected and median values and the 5%–95% and 25%–75% percentile intervals are shown for cases A and B.

Table 4
Generation capacity and marginal cost of each generator.

Node n	Zone	Generation capacity [MW]	Marginal cost MC_n [€/MWh] Set-up a	Set-up b
1	A	500	0	0
2	A	250	20	40
3	B	250	35	20
4	C	250	40	35

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