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# Enabling inter-area reserve exchange through stable benefit allocation mechanisms☆

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The establishment of a single European day-ahead market has accomplished the integration of the regional day-ahead markets. However, reserve provision and activation remain an exclusive responsibility of regional operators. This limited spatial coordination and the separated structure hinder the efficient utilization of flexible generation and transmission, since their capacities have to be ex-ante allocated between energy and reserves. To promote reserve exchange, recent work proposed a preemptive model that withdraws a portion of the inter-area transmission capacity available from day-ahead energy for reserves by minimizing the expected system cost. This decision-support tool, formulated as a stochastic bilevel program, respects the current architecture but does not suggest area-specific costs that guarantee sufficient benefits for areas to accept the solution. To this end, we formulate a preemptive model in a framework that allows application of game theory methods to obtain a stable benefit allocation, i.e., an outcome immune to coalitional deviations ensuring willingness of areas to coordinate. We show that benefit allocation mechanisms can be formulated either at the day-ahead or the real-time stages, in order to distribute the expected or the scenario-specific benefits, respectively. For both games, the proposed benefits achieve minimal stability violation, while allowing for a tractable computation with limited queries to the bilevel program. Our case studies, based on an illustrative and a more realistic test case, compare our method with well-studied benefit allocations, namely, the Shapley value and nucleolus, and analyze the factors that drive these allocations (e.g., flexibility, network structure, wind correlations). We show that our method performs better in stability and tractability.



## 1. Introduction

The existing market architectures and the predominant models for system balancing were designed in a time when fully controllable generators with nonnegligible marginal costs were prevalent. However, as the increasing shares of variable and partly predictable renewable resources displace controllable generation, the dispatch flexibility decreases, while the operational uncertainty characteristics become increasingly complex. In light of this new operational paradigm, there is an imperative need to re-evaluate the current market design, and there has been a surge of interest in proposing new market frameworks [3,11,17,59].

According to the European electricity market design, the bulk volume of energy trading takes place in the day-ahead market, which is typically cleared 12–36 hours before the actual delivery, based on single-valued point forecasts of the stochastic power output of renewable resources. In turn, a balancing market is cleared close to real-time operation in order to compensate any deviations from the day-ahead schedule. Apart from these energy-only trading floors, a reserve capacity auction is organized, usually prior to the day-ahead market, in order to ensure that sufficient capacity is set aside for the provision of balancing services. Following this sequential and separated clearing approach, the current market structure attains only limited coordination between day-ahead and balancing. Aiming to enhance this temporal coupling, recently proposed dispatch models employ stochastic programming in order to co-optimize the day-ahead and the reserve capacity

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markets [12,16,33,55,56,68,79,80]. However, these approaches cannot be directly applied to the existing European electricity markets, since they would require significant restructuring of the current separated market frameworks. The main philosophy of this separated design has been to simplify trading arrangements aiming to improve market transparency and liquidity. Following the EU target model by the European Commission (EC), it is not expected that such a co-optimization will be implemented in the European market in the foreseeable future [7,24].

In terms of geographical considerations, the European electricity market is fully coordinated only at the day-ahead stage, while reserve capacity and balancing markets are still operated on a country/regional level [21]. However, the EC regulation has already established a detailed guideline [25] that lays out the rules also for the integration of the balancing markets in order to improve the security of supply and the efficiency of the balancing system. In this ongoing process that is expected to be completed by 2023 [31], several questions remain open regarding the specific structure and final coordination arrangement among the ENTSO-E (European Network of Transmission System Operators for Electricity) member countries, since there is no binding legislation that enforces transmission system operators (TSOs) to enter such collaborations. The recent study in [24] to investigate the benefits of different organizational models for the integration of balancing markets, shows that the 10-year net present value (NPV) of coordinated balancing ranges from 1,7 to 3,8 B€, depending on the degree of coordination in the inter-area exchanges, see also [60]. Nonetheless, any regional coordination arrangement in the procurement and activation of reserves depends upon the availability of inter-regional transmission capacity. Given that the energy and reserve capacity markets are cleared sequentially, a portion of this transmission capacity made available to day-ahead energy market have to be withdrawn from day-ahead energy market to be allocated to reserve exchange. The exact methodology for the process of allocating inter-area transmission capacity to reserves remains to be discussed and approved by the ENTSO-E members [32] [26, (14)]. Moreover, an application can be filed by even two or more TSOs. In coalitional game theory, such arrangements would be called coalitional deviations, since they involve only some of the members. Motivated by this, the goal of this paper is to propose a coalitional game-theoretic approach for the design of a transmission allocation mechanism. In order to gain technical and economical insights about such a process, we will analyze different factors such as flexibility, network structure, and wind correlations.

The reservation of inter-area interconnections for reserve exchange withdraws transmission resources from the day-ahead market, where the main volume of electricity is being traded. Currently, these cross-border capacities for the day-ahead market are decided by the TSOs respecting the minimum remaining available margin (minRAM) rule of 70% following the requirements of the Clean Energy Package [26, Article 16(8a-8b)], see [28, §2] for their computation. A sub-optimal reservation for reserves from these day-ahead quantities may lead to significant efficiency losses at the day-ahead stage. To prevent this situation, the Agency for the Cooperation of Energy Regulators (ACER) [2] mandates to perform detailed analyses demonstrating that such reservation from day-ahead market would increase overall social welfare. Up to this date, inter-area transmission capacity is typically not removed from day-ahead energy exchange for reserves. One notable exemption is the Skagerrak interconnector between Western Denmark and Norway, in which 15% of the day-ahead cross-border transmission capacity is permanently set aside for reserve exchange [29]. Nevertheless, this allocation is static, while the true optimum varies dynamically depending on generation, load, and system uncertainties. As such, Delikaraoglou and Pinson [20] developed a preemptive transmission allocation model that defines the optimal inter-area transmission capacity allocation to improve both spatial and temporal coordination at the reserve procurement stage.

The recently proposed preemptive transmission allocation model of Delikaraoglou and Pinson [20] focuses on the minimization of the expected system cost, assuming implicitly full coordination among the regional operators. This assumption is in line with the current state of the day-ahead market, which is fully integrated across Europe, or even for the balancing markets in certain regions, e.g., in the Nordic system all reserve activation offers are pooled into a common merit-order list and are available to all TSOs [10]. This assumption allows us to model each of these three trading floors by one respective optimization problem, which would not be possible in case of partial coordination. However, the initial version of the preemptive model does not suggest an area-specific cost allocation which guarantees that all areas have sufficient benefits to accept the proposed solution. This would be concerning for the fairness of the future integrated balancing markets. In particular, the stakeholder document from the International Grid Control Cooperation (IGCC) [39, §6], developed by ten European operators, describes analytically a fair settlement scheme for the simpler setting of imbalance netting process. Again for the imbalance netting problem, market stakeholders have already recognized that the generated financial benefits should be shared among the participating TSOs in a way that every TSO and also its area (which includes producers, load serving entities, and the consumer base) benefit from the cooperation and have the incentive to continue their participation [5]. Here, the benefits correspond to the reductions in the total cost allocated to an area from all three stages of the sequential market, whereas the cost refers to minus the social welfare, which is given by the sum of the consumers' and generators' surplus pertaining to that area and the congestion rents collected by the corresponding area operator. These definitions of benefits and costs were established in Kristiansen et al. [49] for allocating benefits from new interconnections.

To address this issue, we integrate the preemptive model in a mathematical framework that allows the application of tools from coalitional game theory in order to obtain a stable benefit allocation, i.e., sufficient benefits providing immunity to coalitional deviations ensuring that all areas are willing to coordinate via the preemptive model. The concepts from coalitional game theory have recently been widely used in the energy community. The Shapley value has been employed in problems regarding the distribution of social welfare among TSOs participating in an imbalance netting cooperation [5] as well as the benefit allocation in transmission network expansion [69] and in cross-border interconnection development [49]. Other applications of the Shapley value in the energy field include cooperation problems in the Eurasian gas supply system [58] and the $CO_2$ emissions abatement in mainland China [37]. However, the Shapley value is in general not within the core, i.e., the set of stable outcomes. Baeyens et al. [6] shared the expected profits from aggregating wind power generation using the core benefit allocations, whereas a similar concept was applied for prosumer cooperation in a combined heat and electricity system in [54], and for cross-border transmission expansion in Northeast Asia in [14].[1]

[1] In most of these works from coalitional game theory literature, each player is captured by an ensemble of agents with potentially different interests. Similarly, in our case, the benefits will be allocated to the areas, and each area is an ensemble of market participants of the corresponding area including TSO, producers, and consumers. This game-theoretic framework ensures the institutional relevance of the overall problem. Even when the main actors involved in the decision-making of a reserve exchange are the TSOs, they are expected to seek the benefits of their areas as a whole [5,39], and they are checked by their relevant regulatory authorities regarding this aspect. Notice that the transmission capacity allocated to the reserve exchange affects the incentive structure of all these market participants.

In contrast to the case studies in the aforementioned works, realistic instances of our problem can exhibit an empty core. To this end, we utilize the least-core as a solution concept, since it achieves minimal stability violation, i.e., minimal benefit improvements from coalitional deviations [53]. To obtain a unique outcome, we propose the approximation of a fairness criterion, which is at the discretion of the regulatory authorities to define. We propose two variations of the benefit allocation mechanism that can be executed either at the day-ahead or the real-time stage to distribute the expected or the actual benefits (i.e., when the uncertainty is revealed), respectively. We illustrate how these two formulations assign either an uncertainty-dependent budget to the regulator/organizer of this reserve exchange and benefit allocation organization, or an uncertainty-dependent benefit to each area participating in reserve exchange. To overcome the exhaustive enumeration of all coalitional deviations, we show that the least-core selecting allocations in this work can be computed efficiently via an iterative constraint generation algorithm. Similar algorithms were utilized to compute an outcome from the core in combinatorial auctions [19] and electricity markets [44]. In contrast, we show that this algorithm can be extended to the least-core in a general non-convex (bilevel) problem, which was, to the best of our knowledge, not formalized previously.

Our contributions are as follows. We formulate the coalition-dependent version of the preemptive transmission allocation model such that we can consider coalitional arrangements between only a subset of operators. This is a novel extension of the model proposed by Delikaraoglou and Pinson [20]. We then study the coalitional game that treats the benefits as an ex-ante process with respect to the uncertainty realization and we provide a condition under which the core is nonempty. Under this condition, it is possible to obtain a stable outcome. In case this condition is not satisfied, we prove that the least-core, which is an outcome that attains minimal stability violation, also ensures the individual rationality property. These two results hold for coalitional games where the coalitional value function is given by a stochastic bilevel optimization problem, and they could be of independent interest for studying similar problems in other domains. We then propose the least-core selecting mechanism as a benefit allocation that achieves minimal stability violation, while enabling the approximation of an additional fairness criterion. In order to implement this mechanism with only a few queries to the preemptive model, we formulate a constraint generation algorithm. This procedure and its convergence for the least-core in our setting are not discussed elsewhere. In addition, we formulate a variation of the coalitional game that allocates the benefits in an ex-post process, which can be applied only after the uncertainty realization is known. For this game, we provide conditions under which the core is empty. We propose an ex-post version of our benefit allocation mechanism. The ex-ante and ex-post versions of this mechanism can achieve the same fundamental properties for the areas either for every uncertainty realization or in expectation, respectively. Finally, we provide techno-economic insights on the factors that drive benefit allocations first with an illustrative three-area nine-node system and then with a more realistic case study based on a larger IEEE test system.

The remainder of this paper is organized as follows. Section 2 describes the organizational structure and introduces a set of necessary assumptions to obtain tractable models. Section 3 discusses the issues related to reserve exchanges and motivates the formulation of the preemptive transmission allocation model. Section 4 introduces necessary background from coalitional game theory, whereas Section 5 focuses on the games arising from the preemptive model, which provide the basis for the benefit allocation mechanisms that accomplish the implicit coordination requirements outlined in the previous section. The numerical case studies are presented in Section 6 and Section 7 concludes the paper and gives suggestions for future work. Appendices are provided in the supplementary material, and can be downloaded from Omega.

## 2. Electricity market framework

### *2.1. Sequential and separated electricity market design and modeling assumptions*

The existing market design based on the sequential and independent clearing of reserves, day-ahead, and balancing markets suffers from two main caveats that become increasingly pronounced as we move towards larger shares of renewable energy production. On the one hand, the day-ahead schedule is optimized based on purely deterministic inputs, i.e., single-valued forecasts of renewables. As a result, the day-ahead market is not responsive to the uncertainty associated with the forecast errors and thus it is weakly coordinated with the real-time balancing. On the other hand, the decoupling of energy and upward/downward reserve capacity trading into two independent auctions ignores the substitution and complementary properties of these two services and leads to inefficient reserve procurement and energy schedules. Eliminating this issue requires that the participants are capable of accounting for these properties internally in their trading strategies. However, quantifying such opportunity costs is a challenging problem, see Swider and Weber [77]. This is a fundamental issue and an inherent suboptimality in the European market framework that emerges from the separation of energy and reserve trading floors, as opposed to the co-optimization of these services in the US-market types. The EU target models still maintain this separated design architecture [7,24].

From a theoretical perspective, these two issues can be contained if reserve capacity procurement, day-ahead energy schedules, and real-time re-dispatch actions are jointly optimized based on a probabilistic description of the uncertainty, see Morales et al. [55], Pritchard et al. [68]. However, the adoption of a stochastic dispatch model as a market-clearing algorithm requires significant restructuring of the current market framework, and poses several computational challenges when it is applied to real-life scale power systems. Owing to restructuring and computational issues, we restrict ourselves to the status-quo market architecture and we embody its design attributes in our methodology while aiming to mitigate the resulting inefficiencies. In order to enable the inter-area exchange of reserves towards a more efficient decoupled market structure, the operator will need to withdraw a certain share of the interconnection capacities from the day-ahead energy trading and then use this headroom for the interconnections in the reserve capacity market.

In the following, we build the mathematical models of the different trading floors based on a set of assumptions that allows us to capture the main attributes of the European market, while maintaining tractability. In line with the current practice, we consider a zonal network representation during the reserve procurement, however, the full network topology is taken into account in the day-ahead and the balancing market-clearing models, using a DC power flow approximation. Note that our network model can be readily adapted to a zonal day-ahead market, for instance, where the inter-zonal transmission energy flows are constrained by the available transfer capacity (ATC) or by a flow-based domain. The challenge would be additional complexity originating from parameter choices for modelling the zonal day-ahead market, as well as the unscheduled flows and congestion to be tackled by counter-trading or re-dispatching in the balancing stage. Using a full network representation, i.e., nodal pricing, both in the day-ahead and the balancing markets eliminates potential discrepancies that may arise due to idiosyncratic congestion effects and allows us to concentrate on issues related to reserves exchange and transmission capacity reservation. Moreover, for the flow-based domain, Marien et al. [52] show that the parameter choices can lead to very different market exchanges and prices. We also refer to Solis [75] for numerical results illustrating this paradigm, and to CREG [18], EI and NVE [27] for discussions on this sensitivity. Since this work focuses on transmission allocation issues concerning primarily the operators, we believe that allowing for a more complete network representation and judiciously abstracting certain details of the real-world operation do not undermine our main goal, that is, the development of a decision-support tool that provides techno-economical insights on reserves exchange and transmission capacity allocation. As a remark, due to these reasons, many studies that focus on renewable integration and coordination analyses commonly ignore the zonal day-ahead market design. Instead, they either assume a nodal market similar to our work [21,50,51], or they implement a simple transportation network ignoring zonal congestion [45,76]. Nonetheless, for the sake of completeness, we will also provide a detailed zonal model when discussing the day-ahead market. Our conclusions would still generalize to such models, since our model is replicating the main imperfections of the current design: the reaction of the market to its parametric decisions originating from the separate trading of energy and reserves.

On the generation side, we consider that all market participants are perfectly competitive. Day-ahead energy offers are submitted in price-quantity pairs that internalize the marginal production cost as well as the unit commitment and inter-temporal constraints, e.g., ramping limits, in accordance with the portfolio bidding practice in the European market. For instance, the Nordic market (NordPool) use primarily such a portfolio bidding principle according to which each market player submits one hourly offer for its whole aggregated portfolio instead of a unit-specific offer. In addition to single hour portfolio offers, market participants may also be allowed to submit more complex offers (the so-called 'block orders') that implicitly incorporate generator ramping limits and multi-period cost structures related to on/off status of the units. However, block orders are outside the scope of this paper. The interested reader is referred to Biskas et al. [9] for different types of block orders and their mathematical formulation. Having this assumption ensures computational tractability by removing separate products that create non-convexities at the day-ahead stage. For similar modelling practices, we refer to Domínguez et al. [21], Poplavskaya and De Vries [67]. Regarding other implications of a day-ahead market that does not model non-convexities we discussed above, we would like to refer to the literature on self-commitment and self-scheduling practices. The former practice refers to the case where a participant fixes its unit commitment status outside the market problem, and the latter practice refers to the case where a participant fixes not only its unit commitment status but also its dispatch quantity outside the market problem. It is known that even a non-convex day-ahead market not modeling cost structure accurate enough (and/or with a horizon not long enough) may incentivize a market participant with complicated cost structure to assume the risk of self-commitment or self-scheduling. Moreover, in the US market, it is observed that a significant number of producers are self-committing or self-scheduling, which is attributed additionally to the volatility of real-time prices and to the fact that day-ahead market clearing relies only on expected values with its deterministic formulation. However, such strategic decisions concerning participants are outside the scope of this paper. For these two aspects, we refer to the works of Pan and Guan [62], Papavasiliou et al. [65]. Papavasiliou et al. [65] present a stochastic programming model for self-commitment under price volatility and risk aversion, where it is shown that less risk aversion results in increased incentives for self-commitment. With regard to the self-scheduling approach, a stochastic optimal strategy of a producer is proposed by Pan and Guan [62] via a computationally efficient implementation of a scenario tree-based multistage stochastic program.

We assume that the reserve capacity offer prices provide adequate incentives to the flexible generators for the provision of real-time balancing services such that the prices of up and down redispatches are the same as the marginal prices in the day-ahead stage, similar to Ahmadi-Khatir et al. [4]. As a remark, if this assumption is not stated, it could be that the bidders strategize and bid differently in the real-time balancing market to make up for their opportunity cost miscalculations at the reserve market stage. In any case, our model is general enough and can readily accept balancing offers with price premiums, i.e., up/down regulating offer prices higher/lower than the day-ahead offer. This technicality will not have any profound impact on our analysis.

In terms of stochastic renewable in-feed, we focus on wind power generation and we model forecast errors using a finite set of scenarios, see for instance Wang and Deng [78]. Assuming null production costs, the corresponding offer price and the spillage cost are set equal to zero. On the consumption side, we consider inelastic demand with a large penalty on lost load and thus the social welfare maximization becomes equivalent to the cost minimization. Finally, we assume that the current implementation of the sequential market provides a budget balanced method to allocate the system cost to all the areas, i.e., the costs of the reserve capacity market, the day-ahead market and the balancing market are allocated to the areas without any deficit or surplus. In the numerics, for the case of no inter-area exchange of reserves, we provide and discuss one such allocation method based on the zonal and nodal prices that assigns producer and consumer surpluses to their corresponding areas, and divides the congestion rent equally between the adjacent areas, see Kristiansen et al. [49] and Section 6.1.

### 2.2. Mathematical formulation

#### 2.2.1. Reserve capacity market

For all the models, notation is stated in Appendix A. Having as a fixed input the upward/downward reserve requirements $RR_a^+/RR_a^-$ in each area $a$ and a pre-defined share $\chi_e$ of the transmission capacity of each inter-area link $e$ allocated to reserves, the reserve market clearing is formulated as:

$$\underset{\Phi_R}{\text{minimize}} \quad \sum_{i\in\mathscr{I}} \left(C_i^+ r_i^+ + C_i^- r_i^-\right) \tag{1a}$$

$$\text{subject to} \quad \sum_{i\in\mathscr{M}_a^{\mathscr{I}}} r_i^+ + \sum_{e\in\mathscr{E}} \mathscr{H}(e,a) r_e^+ \geq RR_a^+, \quad \forall a\in\mathscr{A}, \tag{1b}$$

$$\sum_{i\in\mathscr{M}_a^{\mathscr{I}}} r_i^- + \sum_{e\in\mathscr{E}} \mathscr{H}(e,a) r_e^- \geq RR_a^-, \quad \forall a\in\mathscr{A}, \tag{1c}$$

$$0\leq r_i^+ \leq R_i^+, \quad \forall i\in\mathscr{I}, \quad 0\leq r_i^- \leq R_i^-, \quad \forall i\in\mathscr{I}, \tag{1d}$$

$$-\chi_e T_e \leq r_e^+ \leq \chi_e T_e, \quad \forall e\in\mathscr{E}, \quad -\chi_e T_e \leq r_e^- \leq \chi_e T_e, \quad \forall e\in\mathscr{E}, \tag{1e}$$

where $\Phi_R = \{r_i^+, r_i^-, \forall i; r_e^+, r_e^-, \forall e\}$ is the set of optimization variables. The objective function (1a) to be minimized is the cost of reserve procurement. Constraints (1b) and (1c) ensure, respectively, that the upward and downward reserve requirements of each area are satisfied either by procuring reserve capacity from intra-area generators or via inter-area reserves exchange that is modeled using the incidence matrix $\mathscr{H}(e,a)$. As shown in Appendix A, for each link $e$ with sending and receiving ends in areas $a_s(e)$ and $a_r(e)$, respectively, $\mathscr{H}(e,a)$ is equal to 1 (-1) if reserve import (export) is considered from (to) area $a = a_s(e)$ $(a = a_r(e))$ and zero for any other area. With this definition, availability of cross-border reserves within the neighboring areas for each area $a$ is modeled by (1b) and (1c). We underline that directed links are used as a notational convention, and both $r_e^+$ and $r_e^-$ are free of sign. Upward and downward capacity offers of dispatchable power plants are enforced by constraints (1d). In the numerics, these capacities will be chosen small enough (e.g., half total capacity) such that both upward and downward reserves can be procured from the power plants in a feasible manner.

The set of constraints (1e) models the bounds on reserves exchange between two areas across link $e$. Following the current practice, we consider a zonal network representation for the reserve capacity markets and thus the transmission capacity $T_e$ of link $e$ is defined as the aggregated flow limit of all tie-lines $\ell \in \Lambda_e$ across link $e$ calculated as $T_e = \sum_{\ell \in \Lambda_e} T_\ell$, for all $e \in \mathscr{E}$. Setting the transmission capacity allocation $\chi_e$ to any value different than zero, establishes practically a reserve exchange mechanism between the areas located at the two ends of the link and consequently it enables the exchange of balancing services during real-time operation. On the contrary, setting $\chi_e = 0$ implies that there would be no reserve exchange at the procurement stage, i.e., the cross-border transmission capacity is fully allocated to day-ahead energy exchanges. In that case, we also prevent the exchange of balancing services and the imbalance netting between the adjacent areas, as we will formally describe in the balancing market model formulation below.

#### 2.2.2. Day-ahead market

Given the optimal reserve procurement $\hat{\Phi}_R = \{\hat{r}_i^+, \hat{r}_i^-, \forall i; \hat{r}_e^+, \hat{r}_e^-, \forall e\}$ from the reserve capacity market, the day-ahead schedule is the solution to the following optimization problem:

$$\underset{\Phi_D}{\text{minimize}} \quad \sum_{i \in \mathscr{I}} C_i p_i \tag{2a}$$

$$\text{subject to} \quad \sum_{j \in \mathscr{M}_n^{\mathscr{J}}} w_j + \sum_{i \in \mathscr{M}_n^{\mathscr{I}}} p_i - \sum_{\ell \in \mathscr{L}} A_{\ell n} f_\ell = D_n, \quad \forall n \in \mathscr{N}, \tag{2b}$$

$$\hat{r}_i^- \le p_i \le P_i - \hat{r}_i^+, \quad \forall i \in \mathscr{I}, \quad 0 \le w_j \le \overline{W}_j, \quad \forall j \in \mathscr{J}, \tag{2c}$$

$$f_\ell = B_\ell \sum_{n \in \mathscr{N}} A_{\ell n} \delta_n, \quad \forall \ell \in \mathscr{L}, \quad -(1-\chi_\ell)\, T_\ell \le f_\ell \le (1-\chi_\ell)\, T_\ell, \quad \forall \ell \in \mathscr{L}, \tag{2d}$$

$$\delta_1 = 0, \quad \delta_n \text{ free}, \quad \forall n \in \mathscr{N}, \tag{2e}$$

where $\Phi_D = \{p_i, \forall i; w_j, \forall j; \delta_n, \forall n; f_\ell, \forall \ell\}$ is the set of variables. Define $\chi_\ell = \chi_e$ for all tie-lines $\ell \in \Lambda_e$ and $\chi_\ell = 0$ for all intra-area lines. For the remainder, we strictly follow this notation. The objective is the day-ahead cost of energy production. Constraints (2b) enforce the day-ahead power balance for each node. The upper and lower production limits of dispatchable power plants are enforced by (2c), taking into account the reserve schedule from the previous trading floor. Constraints (2c) also limit the stochastic production to a point forecast, typically the expected value of the stochastic process. Power flows are first computed in (2d) and then restricted by the capacity limits considering that $(1-\chi_\ell)$ percent of the capacity is available for day-ahead energy trade. This is because a $\chi_\ell$ portion of the cross-border transmission resource made available is withdrawn from day-ahead energy to instead be allocated to reserves, following the regulations [32]. As previously discussed, the current practice is in fact a zonal hybrid where the flows are constrained by the available transmission capacity or a flow-based domain. In the case of a zonal market, this could be a portion of the cross-border transmission capacities computed for the day-ahead market respecting the minRAM rule of 70% in [26, Article 16(8a-8b)] [28, §2]. (Note that the minRAM rule may also be applied after the reservation of a transmission share for reserves exchange.) Our method can also be readily adapted to the zonal scheme. We present in detail the integration of a zonal market into our method in Appendix B. Finally, the voltage angle at node 1 is fixed to zero in (2e) setting this as the reference node, whereas the remaining voltage angles are declared as free variables.

#### 2.2.3. Balancing market

Being close to real-time operation uncertainty realization $s'$ and actual wind power production $W_{js'}$, $\forall j \in \mathscr{J}$ are known. Any energy deviations from the optimal day-ahead schedule $\hat{\Phi}_D = \{\hat{p}_i, \forall i; \hat{w}_j, \forall j; \hat{\delta}_n, \forall n; \hat{f}_\ell, \forall \ell\}$ must be contained using proper re-dispatch actions that respect the reserve procurement schedule $\hat{\Phi}_R$. To determine the re-dispatch actions that minimize the balancing cost, the balancing market is cleared based on the following optimization problem:

$$\underset{\Phi_B^{s'}}{\text{minimize}} \quad \sum_{i \in \mathscr{I}} C_i \left(p_{is'}^+ - p_{is'}^-\right) + \sum_{n \in \mathscr{N}} C^{\text{sh}} l_{ns'}^{\text{sh}} \tag{3a}$$

$$\text{subject to} \quad \sum_{i \in \mathscr{M}_n^{\mathscr{I}}} \left(p_{is'}^+ - p_{is'}^-\right) + l_{ns'}^{\text{sh}} + \sum_{j \in \mathscr{M}_n^{\mathscr{J}}} \left(W_{js'} - \hat{w}_j - w_{js'}^{\text{spill}}\right) + \sum_{\ell \in \mathscr{L}^{\text{AC}}} A_{\ell n}\left(\hat{f}_\ell - f_{\ell s'}\right) = 0, \ \forall n \in \mathscr{N}, \tag{3b}$$

$$0 \le p_{is'}^+ \le \hat{r}_i^+, \quad \forall i \in \mathscr{I}, \quad 0 \le p_{is'}^- \le \hat{r}_i^-, \quad \forall i \in \mathscr{I}, \tag{3c}$$

$$0 \le l_{ns'}^{\text{sh}} \le D_n, \quad \forall n \in \mathscr{N}, \quad 0 \le w_{js'}^{\text{spill}} \le W_{js'}, \quad \forall j \in \mathscr{J}, \tag{3d}$$

$$f_{\ell s'} = B_\ell \sum_{n \in \mathscr{N}} A_{\ell n} \delta_{ns'}, \quad \forall \ell \in \mathscr{L}, \quad -T_\ell \le f_{\ell s'} \le T_\ell, \quad \forall \ell \in \mathscr{L}, \tag{3e}$$

$$f_{\ell s'} = \hat{f}_\ell, \quad \forall \ell \in \cup_{e \in \mathscr{E}^-(\chi)} \Lambda_e, \quad \delta_{1s'} = 0, \quad \delta_{ns'} \text{ free}, \quad \forall n \in \mathscr{N}, \tag{3f}$$

where $\Phi_B^{s'} = \{p_{is'}^+, p_{is'}^-, \forall i; w_{js'}^{\text{spill}}, \forall j; l_{ns'}^{\text{sh}}, \delta_{ns'}, \forall n; f_{\ell s'}, \forall \ell\}$ is the set of variables. The objective is the cost of re-dispatch actions, i.e., reserve activation and load shedding. Up and down re-dispatch actions have the same cost as their day-ahead energy market counterpart, under the assumption that the reserve market price is enough to compensate for the opportunity cost from withdrawing capacity from the day-ahead stage, see Section 2.1. Equality constraints (3b) ensure that all the nodes remain in balance after the re-dispatch of generation and any necessary wind power curtailment or load shedding. Constraints (3c) ensure that upward and downward reserve deployment respects the corresponding procured quantities. The upper bounds on load shedding and power spillage are set equal to the nodal demand and the realized wind power production by constraints (3d).

Real-time power flows are first modeled and then restricted by the transmission capacity limits in (3e). Constraints (3f), where $\mathscr{E}^-(\chi) = \{e \in \mathscr{E} \,|\, \chi_e = 0\}$ denotes the set of inter-area links with no existing cross-border agreement across them, ensure that if $\chi_e = 0$, this link and the connected areas do not participate in the reserve exchange and in the imbalance netting processes. In the existing market (with a zonal day-ahead market), the balance responsible parties are entitled to maintain their scheduled day-ahead net positions in the real-time market [30], [23, Article 17]. Since our day-ahead market is modeled by a nodal market and $\hat{f}_\ell$ are already well-defined, we translate this regulation as preventing any reserve sharing or imbalance netting during real-time operation across any line within link $e$ if $\chi_e = 0$ (in other words the real-time flows on the tie lines are fixed to their day-ahead values). For similar requirements, see Elia et al. [28, §2.3], Solis [75, §4.A.7]. In order to tailor our model even more to the European market idiosyncrasies, Appendix B provides zonal day-ahead market models, and it explains how we can represent the links and areas that are not participating in cross-border exchange in balancing market stage (for instance, by maintaining only the net positions of areas/zones). We would like to highlight that it is straightforward to handle such constraints also in the zonal setting. Finally, node 1 is again the reference node.

## 3. Transmission capacity allocations for cross-border balancing

### 3.1. Coordination schemes and transmission allocation arrangements for cross-border trading

The transition to an integrated balancing market requires several organizational changes to the prevailing operational model, in which reserves are procured and deployed on an intra-area basis. A prerequisite for the establishment of a well-functioning balancing framework is the standardization of the rules and products as well as the definition of transparent mechanisms that will facilitate the cooperation among the TSOs [38]. Below, we outline the main coordination schemes and transmission allocation arrangements as defined in the current European regulation [25].

Inter-area reserve procurement can be organized as a reserve exchange scheme and/or as a reserve sharing agreement. Implementing the former scheme, regional TSOs can procure balancing capacity resources located in adjacent areas in order to meet their own area reserve requirements. Since the reserve requirements of each area remain unchanged, this coordination setup requires limited organizational changes, as it basically reallocates the reserve quantities towards areas with lower procurement costs. To improve also the dimensioning efficiency of the procurement process, a reserve sharing agreement allows a TSO to use available reserve capacity from adjacent TSOs. An implied prerequisite for this arrangement would be that the definition of regional reserve requirements is performed jointly by all TSOs that participate in the sharing agreement. In terms of coordination during reserves activation, the main organizational setups are the so-called imbalance netting and exchange of balancing energy. The first setup pertains to the inter-area exchange of imbalances with opposite sign, thus preventing the counteracting activation of balancing resources and reducing the total balancing energy volumes. In turn, the exchange of balancing energy enables the system-wide least-cost activation of reserves through a common merit-order list to meet the net imbalance of the joint TSO area. This improves the supply efficiency of balancing energy, at the expense of more extensive coordination requirements.

The establishment of any cross-border reserve procurement scheme requires the reservation of a certain share of the inter-area transmission capacity from the day-ahead market for the reserves and their activation EC [26, (14)]. Such a reservation increases the cost of the day-ahead market, but in return decreases the costs for the reserve market and the balancing market. Before we describe the attributes of any specific transmission allocation mechanism, let us provide an illustrative example for the resulting total cost from all three stages. This example highlights the seams issues pertaining to the ex-ante definition of transmission allocation between two neighboring areas. Fig. 1 shows the expected system

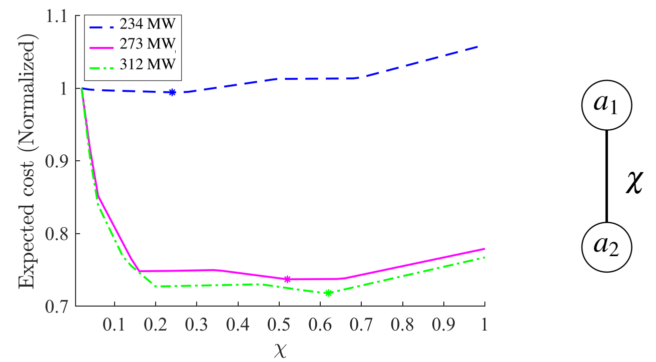


**Fig. 1.** Expected operation cost as a function of transmission capacity allocated to inter-area reserves trading under different levels of wind power penetration (in MW).

cost, i.e., the sum of reserve procurement, day-ahead energy and expected balancing costs, as a function of the share of transmission capacity $\chi$ that is allocated to inter-area reserves trading. The data for this two-area power system is provided in Appendix C, and the models are those that were discussed in the previous section. We can observe that the efficiency of an integrated market, in terms of expected system cost defined above, is highly susceptible to the portion $\chi$ of transmission capacity removed from the day-ahead market. Moreover, its optimal value minimizing the cost changes significantly under different levels of wind power penetrations. Even from this simple example, it becomes apparent that there exists an optimal allocation to be made, which however may dynamically vary depending on generation, load and system uncertainties. This in turn asks for a systematic method to optimally define $\chi$, accounting for the market dynamics and the uncertainty involved in the operation of the power system.

In this work, we focus on the prevailing methodology for the allocation of cross-border transmission capacity from day-ahead energy to reserves. According to this methodology, a share of inter-area transmission capacity is expected to be set aside from day-ahead energy for reserves based on the comparison of the market value of cross-zonal capacity for the exchange of balancing capacity or sharing of reserves and the market value of cross-zonal capacity for the exchange of day-ahead energy.[2] This methodology can attain a reasonable allocation efficiency while having practical applicability within the current framework, albeit it still incurs the inherent drawbacks of the sequential and separated market structure regarding the deterministic view of uncertainty and the separation of energy and reserve services. We refer the interested reader to EC [25] for discussions on alternative transmission allocation mechanisms.

### 3.2. Preemptive transmission allocation model

In this section, we first describe the preemptive transmission allocation model that was initially proposed in Delikaraoglou and Pinson [20]. This work, however, defines the preemptive model in a more general framework, which allows us to consider coalitional deviations and in turn define the necessary benefits that support the solution proposed by the preemptive model. The motivation for considering coalitional deviations originates from the Clean Energy Package regulation which states that an application for a method-

[2] This methodology can either be implemented by an implicit auction solving a centralized optimization problem, or by an explicit auction where each area can submit its own valuation to a market organizer establishing a new trading floor as in [42]. Our mechanism corresponds to an implicit auction, see the discussions in Section 3.3.

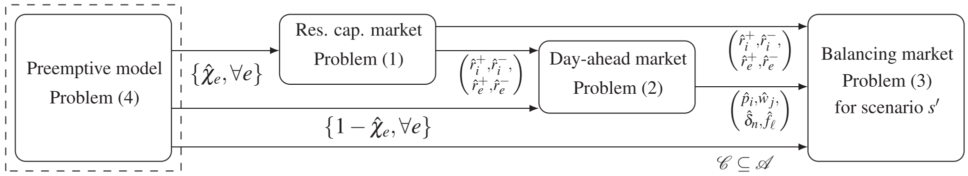


**Fig. 2.** Schematic representation of preemptive transmission allocation model.

ology of allocating cross-border capacity to reserves can be filed by even two neighboring operators [26, (14)].

The preemptive transmission allocation model can be perceived as a decision-support tool, which aims at defining the optimal shares of transmission capacity for inter-area trading of energy and reserves. Being fully aligned with the existing sequential market structure, the preemptive model is essentially a transmission allocation process that is performed prior to the reserve capacity and day-ahead energy market clearings to find the optimal transmission allocations $\{\hat{\chi}_e, \forall e\}$ that minimize the expected system cost, see Fig. 2.[3]

In this work, the focus is on the establishment of coalitional agreements at the reserve procurement stage among a set of areas $\mathscr{C} \subseteq \mathscr{A}$. In the balancing market, we assume that all areas that participate in the coalition, exchange balancing energy in a perfectly coordinated setup. As a result, real-time tie-line flows are treated as free variables, allowing for deviations from the day-ahead schedule. The coalition-dependent preemptive model is given by:

$$J(\mathscr{C}) = \underset{\Phi_{\text{PR}}}{\text{minimize}} \quad \sum_{i\in\mathscr{I}} \left(C_i^+ r_i^+ + C_i^- r_i^-\right) + \sum_{i\in\mathscr{I}} C_i p_i + \sum_{s\in\mathscr{S}} \pi_s \left[ \sum_{i\in\mathscr{I}} C_i \left(p_{is}^+ - p_{is}^-\right) + \sum_{n\in\mathscr{N}} C^{\text{sh}} l_{ns}^{\text{sh}} \right] \tag{4a}$$

$$\text{subject to} \quad 0 \le \chi'_e \le 1, \quad \forall e \in \mathscr{E}_{\mathscr{C}}, \tag{4b}$$

$$\chi'_e = \chi_e, \quad \forall e \in \mathscr{E} \setminus \mathscr{E}_{\mathscr{C}}, \tag{4c}$$

$$\text{Constraints (3b)} - \text{(3e) and } \delta_{1s} = 0,\ \delta_{ns} \text{ free},\ \forall n \in \mathscr{N}, \quad \forall s \in \mathscr{S}, \tag{4d}$$

$$f_{\ell s} = f_\ell, \quad \forall \ell \in \cup_{e\in\mathscr{E}^-(\chi,\mathscr{C})} \Lambda_e, \quad \forall s \in \mathscr{S}, \tag{4e}$$

$$\begin{pmatrix} r_i^+, r_i^-, \\ r_e^+, r_e^- \end{pmatrix} \in \arg\left\{ \underset{\Phi_{\text{R}}}{\text{minimize}} \quad (1a) \quad \text{subject to constraints (1b) - (1e)} \right\}, \tag{4f}$$

$$\begin{pmatrix} p_i, w_j, \\ \delta_n, f_\ell \end{pmatrix} \in \arg\left\{ \underset{\Phi_{\text{D}}}{\text{minimize}} \quad (2a) \quad \text{subject to constraints (2b) - (2e)} \right\}, \tag{4g}$$

where $\Phi_{\text{PR}} = \{\chi'_e, \forall e \cup \Phi_{\text{R}} \cup \Phi_{\text{D}} \cup \Phi_{\text{B}}^s, \forall s\}$ is the set of primal optimization variables. For the sake of brevity, the Lagrange multipliers of the lower-level optimization problems are omitted here, but the complete set of Karush-Kuhn-Tucker (KKT) conditions of problems (1) and (2) are listed in Appendix D. Unless stated otherwise, the preemptive model refers to problem (4) associated with $J(\mathscr{A})$ and the corresponding optimal transmission allocation is denoted by $\{\hat{\chi}_e, \forall e\}$.

Model (4) is a stochastic optimization problem, since wind power is described by a finite set of scenarios $\mathscr{S}$, with $W_{js}$ being the realization of stochastic generation of farm $j$ in scenario $s$ and $\pi_s$ the corresponding probability. The objective is the expected system cost according to the sequential structure described in Section 2.2. Constraint (4b) bounds the share of transmission capacity $\chi'_e \in [0, 1]^{\mathscr{E}}$ allocated to reserve exchange for links $e \in \mathscr{E}_{\mathscr{C}}$, where $\mathscr{E}_{\mathscr{C}} = \{e \,|\, \mathscr{H}(e, a) = 0,\ \forall a \in \mathscr{A} \setminus \mathscr{C}\}$ is the set of links among only the areas in the coalition $\mathscr{C}$. The transmission capacity of the remaining links $e \in \mathscr{E} \setminus \mathscr{E}_{\mathscr{C}}$, i.e., links that are connected to areas that are not members of coalition $\mathscr{C}$, is fixed according to existing cross-border agreements $\chi_e \in [0, 1]^{\mathscr{E}}$ in (4c). Constraints (4d) ensure feasibility of re-dispatch actions for each scenario, whereas constraint (4e) restricts the real-time tie-line flows to the respective day-ahead values, for links $e \in \mathscr{E}^-(\chi, \mathscr{C}) = \{e \in \mathscr{E} \,|\, \chi_e = 0, \text{ and } \exists a \in \mathscr{A} \setminus \mathscr{C} \text{ such that } \mathscr{H}(e, a) \neq 0\}$, which is the set of links that are, at least on one end, connected to an area that is not in the coalition $\mathscr{C}$ and does not have an existing cross-border agreement for reserves exchange, i.e., $\chi_e = 0$. In other words, constraint (4e) prevents any imbalance netting or exchange of balancing energy between areas that are not members of coalition $\mathscr{C}$. We kindly refer to Appendix B for explanations on how we can represent such constraints when the day-ahead market is zonal (for instance, by maintaining net positions of zones). Constraints (4e) are removed from problem (4) associated with $J(\mathscr{A})$, since $\mathscr{E}(\chi, \mathscr{A}) = \emptyset$ for any $\chi$.

The lower-level problems (4f) and (4g) are identical to models (1) and (2) implementing the shares of transmission capacities in $\chi'$. Having this bilevel model (4) ensures by construction that the reserve capacity, day-ahead and balancing markets are cleared in consecutive and independent auctions. This structure allows the definition of $\{\hat{\chi}_e, \forall e\}$ anticipating the impact of these parameters in all subsequent trading floors. From a computational perspective, to obtain a solvable instance of the model (4), we can equivalently replace the lower-level problems (4f) and (4g) by the KKT conditions, given that (4f) and (4g) are linear programs. The resulting problem is a single-level mathematical program with equilibrium constraints (MPEC) that involves the complementary slackness constraints, which can be transformed into a mixed-integer linear program (MILP) using disjunctive constraints. We refer to Appendix D for the KKT conditions of (1) and (2).

Regarding the structure of the bilevel model (4), in contrast to the reserve capacity and the day-ahead markets, the balancing market is modeled in the upper-level by the last term of the objective (4a) and constraints (4d)-(4e). The proposed structure leverages the fact that the variables of the balancing market in (3) do not enforce any restriction on the upper-level variables $\{\chi'_e, \forall e\}$ and also they do not impact the lower-level problems (4f) and (4g). Following this observation, our formulation reduces the computational complexity of the final MILP, since it avoids the integer reformulation of the balancing market complementarity conditions for each scenario. We provided a mathematical explanation in Appendix D. For relevant applications of bilevel programming, kindly

[3] It is worth mentioning that the coordinated reserve exchange would require a transfer of some responsibilities to European bodies, even though some TSOs might be hesitant to assign some of their autonomy to a central authority.

refer to Grimm et al. [35], Morales et al. [57], Pineda and Morales [66], Soares et al. [74].

Having defined the main properties of the preemptive model, the following comments are in order. Define the sum of the costs (1a), (2a) and (3a), as $J^{s'}(\emptyset)$ and $J^{s'}(\mathscr{A})$, when $\chi_e, \forall e$ are fixed to the existing cross-border arrangements and to the optimal $\{\hat{\chi}_e, \forall e\}$ from the preemptive model, respectively. From an economic intuition, it follows that the preemptive model reduces the total expected cost since the establishment of broader coalitions enlarges the pool of available reserves and balancing resources, and enables the more efficient allocation of available generation capacity between these services. This can be mathematically stated as $J(\mathscr{A}) = \mathbb{E}_s[J^s(\mathscr{A})] \leq J(\emptyset) = \mathbb{E}_s[J^s(\emptyset)]$, where $\mathbb{E}_s[\cdot]$ is the expectation calculated over the scenario set $\mathscr{S}$. Using a similar reasoning, it follows that $J$ is a nonincreasing function with respect to the number of areas participating in the coalition, i.e., $J(\mathscr{C}) \leq J(\hat{\mathscr{C}})$ for all $\hat{\mathscr{C}} \subseteq \mathscr{C}$. (Note that the preemptive model does not guarantee $J^s(\mathscr{C}) \leq J^s(\hat{\mathscr{C}})$, $\forall \hat{\mathscr{C}} \subseteq \mathscr{C}$ for each scenario independently.) It becomes apparent that the implementation of the preemptive model results in a different system cost than the one under the current sequential market. Next, we discuss cost allocation in this new sequential market.

### 3.3. Cost allocation for the preemptive model

The preemptive model (4) implements a centralized transmission allocation mechanism, under the implicit assumption that all areas are willing to accept the $\{\hat{\chi}_e, \forall e\}$ solution that by construction minimizes the system-wide expected cost. However, this model does not suggest an area-specific cost allocation that guarantees sufficient benefits for all areas to remain in the grand coalition $\mathscr{A}$.[4] The task of setting the transmission shares and allocating the resulting costs could be accomplished through establishing a new market, cleared before the reserve market, in which regional operators would place their bids/offers for the reservation of inter-area transmission capacities, akin to the decision variable of the preemptive model, $\{\chi'_e, \forall e\}$. This new market would constitute an ideal benchmark of the market-based allocation process described in EC [25], implementing a *complete* market for transmission allocations in which capacities would be traded based on bids/offers that reflect the valuations from regional operators [42]. In this work, we follow an alternative path to promote the formation of stable coalitions for the exchange of reserves. Our approach builds an ex-post benefit allocation mechanism on top of the preemptive model, aiming to realize the necessary conditions that accomplish the coordination requirements of this model, without any new marketplace. In the remainder, we outline the concepts related to benefit allocations for the preemptive model and we discuss the desirable properties that we want to achieve.

Let $J_a^s(\emptyset)$ denote the cost allocated to area $a$ in scenario $s$ in the existing sequential market. As previously discussed, the current implementation of the sequential market provides a cost allocation method that satisfies budget balance under every scenario, i.e., $J^s(\emptyset) = \sum_{a\in\mathscr{A}} J_a^s(\emptyset)$. The implementation of the preemptive model requires a new method to allocate costs to the areas that participate in this arrangement. This task can equivalently be viewed as allocating benefits based on the change in the total cost as a discount or a mark-up on the original cost allocation of each area defined by $J_a^s(\emptyset)$. While choosing these benefits, our main goal is to ensure that all areas in $\mathscr{A}$ are willing to use the preemptive model as a decision-support tool, since otherwise some areas may opt for having their own reserve exchange agreement following EC [26, (14)]. In addition, we should aim to form coalitions as large as possible in order to achieve the highest reduction in the expected system cost. To achieve these, we will treat the preemptive model as a coalitional game, which allows us to approach the benefit allocation problem in two ways. First, we can allocate the expected cost reduction, $J(\emptyset) - J(\mathscr{A}) \geq 0$, to all areas as benefits. Allocating benefits this way achieves budget balance in expectation, which implies that there is no deficit or surplus if the preemptive model is used repeatedly and the uncertainty modeling is accurate enough.[5] However, this method does not guarantee that the resulting allocation satisfies budget balance in every scenario, thus requiring a large financial reserve to buffer the fluctuations in the budget in case of surplus or deficit for some realizations. The second approach is to allocate the scenario-specific cost variation, $J^s(\emptyset) - J^s(\mathscr{A})$. This would guarantee budget balance for every scenario. However, the participating areas would collect benefits that vary under scenarios, possibly raising risk considerations.

As a remark, the benefit allocation framework studied in this paper defines these monetary quantities on an area level. They provide each area with an idealized total cost allocation, which would be minus the sum of three terms, that is, the consumers' and generators' surplus pertaining to that area and the congestion rents collected by the corresponding area operator. We highlight that the methods proposed in this paper do not readily define the payment rules for the new sequential market such that these idealized total cost allocations (or the total available surpluses) are distributed on a market participant level. However, it is possible to provide a guarantee on the cost recovery property of market participants. Later in our work, by picking nonnegative benefits, we in fact guarantee that the available surplus for each area increases. This implies that it is possible to define payment rules to achieve cost recovery, moreover, it is also possible to improve each generator's and consumer's surplus compared to their values in the existing sequential market.[6]

## 4. Coalitional game theory framework

A coalitional game is defined by a set of players and the so-called coalitional value function, that maps from the subsets of players to the values, i.e., the total benefits created by these players. In the preemptive model, the set of players are given by the set of areas $\mathscr{A}$[7], whereas the coalitional value function $v : 2^{\mathscr{A}} \to \mathbb{R}$ can be defined either as the expected cost reduction achieved, i.e., $\bar{v}(\mathscr{C}) = J(\emptyset) - J(\mathscr{C})$, for all $\mathscr{C} \subseteq \mathscr{A}$ or based on the resulting change in the cost of the realized scenario $s \in \mathscr{S}$, i.e., $v^s(\mathscr{C}) = J^s(\emptyset) - J^s(\mathscr{C})$, for all $\mathscr{C} \subseteq \mathscr{A}$. Clearly, it holds that $\bar{v}(\mathscr{C}) = \mathbb{E}_s[v^s(\mathscr{C})]$. Later, we will see that these functions yield different structures for the game. In the remainder of this section, we study a generic $v$ for the preemptive model satisfying $v(\mathscr{C}) = 0$, for all $|\mathscr{C}| \leq 1$. This assumption holds since coordination is not possible in the preemptive model without the participation of at least two adjacent areas.

Given the coalitional value function $v$, *a benefit allocation mechanism* defines the benefit received by each area $a \in \mathscr{A}$ with $\beta_a(v) \in \mathbb{R}$. The cost allocated to area $a$ under the preemptive transmission

[4] As it is introduced earlier, benefits are the change in total operational cost allocated to a particular area after all three market stages are cleared. The operational cost is equivalent to minus the social welfare (with inelastic demand) and thus it is reasonable to define positive benefits as the reduction of the total operational cost.

[5] In practice, the scenario set is inevitably an approximation to the real world. There are various results showing asymptotic guarantees for convex optimization as long as the scenario set is rich enough [8]

[6] If the preemptive model is used and all market stages are cleared with their new unit prices given by the new Lagrange multipliers, then we can obtain cost recovery on a market participant level. However, such an approach cannot provide any guarantees on an area level at all. Defining side payments to ensure that the cost allocation of each area is close what is suggested by the benefit allocation methods is part of our ongoing work.

[7] Areas as a whole (country or region) includes consumers and generators pertaining to that area and area operators (and potentially the transmission owners).

allocation model would then be given by $J_a^s(\mathscr{A}) = J_a^s(\emptyset) - \beta_a(v)$. Depending on its sign, the benefit can be considered as a discount or a mark-up on the original cost allocation. When designing benefit allocation mechanisms, there are three fundamental properties we want to guarantee, namely, efficiency, individual rationality, and stability. A benefit allocation $\beta(v) = \{\beta_a(v)\}_{a\in\mathscr{A}} \in \mathbb{R}^{\mathscr{A}}$ is *efficient* if the whole value created by the grand coalition, i.e., $\mathscr{C} = \mathscr{A}$, is allocated to the member-areas, i.e., $\sum_{a\in\mathscr{A}} \beta_a(v) = v(\mathscr{A})$.[8] A benefit allocation ensures *individual rationality* if all areas obtain nonnegative benefits, i.e., $\beta_a(v) \geq 0$, for all $a \in \mathscr{A}$. If this property does not hold, the coordination arrangement would yield increased costs for some areas. As a result, these areas may decide not to participate in the preemptive model. Finally, a benefit allocation attains *stability* (in other words, group rationality) if it eliminates the benefit improvements of the areas from forming sub-coalitions, i.e., $\nexists \mathscr{C} \subset \mathscr{A}$ such that $v(\mathscr{C}) > \sum_{a\in\mathscr{C}} \beta_a(v)$. This last property is crucial for the preemptive model, since otherwise some areas may opt for having their own reserve exchange agreement by excluding the remaining areas. This coincides with our aforementioned goal of ensuring that all areas participate in the preemptive model.

In coalitional game theory, these properties are known to be attained if the benefit allocation lies in the *core* defined as $\beta(v) \in K_{\text{Core}}(v)$, where $K_{\text{Core}}(v) = \{\beta \in \mathbb{R}^{\mathscr{A}} \mid \sum_{a\in\mathscr{A}} \beta_a = v(\mathscr{A}),\ \sum_{a\in\mathscr{C}} \beta_a \geq v(\mathscr{C}),\ \forall \mathscr{C} \subset \mathscr{A}\}$. In this definition, the equality constraint ensures efficiency, while inequality constraints guarantee stability, i.e., there is no subset of areas $\mathscr{C} \subset \mathscr{A}$ that can yield higher total benefits for its members compared to the benefit allocation under the grand coalition. The inequality constraints also include $\beta_a(v) \geq v(a) = 0$ for all $a \in \mathscr{A}$. (For the sake of simplicity, singleton sets are denoted by $a$ instead of $\{a\}$.) This restriction ensures individual rationality.

The core is a closed polytope involving $2^{|\mathscr{A}|}$ linear constraints. This polytope is nonempty if and only if the coalitional game is balanced [71]. Such settings include the cases in which the coalitional value function exhibits supermodularity[9] and the cases in which the coalitional value function can be modeled by a concave exchange economy [73] or a linear production game [61]. In their most general form, the coalitional value functions in these works are given by an optimization problem minimizing a convex objective subject to linear constraints. In the problem at hand, coalitional value functions are associated with solutions to the general non-convex optimization problem (4). As a result, previous works on the nonemptiness of the core are not applicable to our setup.

In case the core is empty, we need to devise a method to approximate a core allocation. To this end, we bring in the notion of strong $\epsilon$-core, defined in Shapley and Shubik [72] as $K_{\text{Core}}(v,\epsilon) = \{\beta \in \mathbb{R}^{\mathscr{A}} \mid \sum_{a\in\mathscr{A}} \beta_a = v(\mathscr{A}),\ \sum_{a\in\mathscr{C}} \beta_a \geq v(\mathscr{C}) - \epsilon,\ \forall \mathscr{C} \subset \mathscr{A}\}$. This definition can be interpreted as follows. If organizing a coalitional deviation entails an additional cost of $\epsilon \in \mathbb{R}$, coalition values would be given by $v(\mathscr{C}) - \epsilon$ for all $\mathscr{C} \neq \mathscr{A}$. Then, the resulting core would correspond to the strong $\epsilon$-core. For $\epsilon = 0$, we retrieve the original core definition, i.e., $K_{\text{Core}}(v,0) = K_{\text{Core}}(v)$.

Let $\epsilon^*(v)$ be the critical value of $\epsilon$ such that the strong $\epsilon$-core is nonempty, which is mathematically defined as $\epsilon^*(v) = \min\{\epsilon \mid K_{\text{Core}}(v,\epsilon) \neq \emptyset\}$. The value $\epsilon^*(v)$ is guaranteed to be finite for any function $v$ and the set $K_{\text{Core}}(v,\epsilon^*(v))$ is called the *least-core* [53]. Let the excess of a coalition be defined by $\theta(v,\beta,\mathscr{C}) = v(\mathscr{C}) - \sum_{a\in\mathscr{C}} \beta_a$, for any nonempty $\mathscr{C} \subset \mathscr{A}$. In other words, the set $K_{\text{Core}}(v,\epsilon^*(v))$ is the set of all efficient benefit allocations minimizing the maximum excess. If the core is empty, the maximum excess is the maximum violation of a stability constraint. This implies that the least-core achieves an approximate stability property. As a remark, the least-core relaxes also the inequality constraints corresponding to singleton sets $\beta_a \geq v(a) - \epsilon^*(v) = -\epsilon^*(v)$ for all $a \in \mathscr{A}$ since $\epsilon^*(v) > 0$, and hence it yields approximate individual rationality. Finally, if the core is not empty, we have $\epsilon^*(v) \leq 0$ and the least-core is a subset of the core.

With the discussion above, we conclude that whenever the core is empty, we can use the least-core to achieve the second best outcome available, i.e., a benefit allocation which is efficient, approximately individually rational and approximately stable. If in a realistic instance of our problem the core turns out to be empty, by definition this implies that there is no approach/allocation that would ensure that cooperation of all areas is a stable outcome. Under this impossibility result, cooperation of this grand coalition has to be enforced by a regulator, as grand coalition gives us the largest total improvement in social welfare. Towards this goal, least-core presents a reasonable compromise for the different areas to not form subcoalitions. Observe that there are generally many points to choose from the least-core (or the core if it is nonempty) achieving the same fundamental properties. In this case, it could be desirable to require additional intuitively acceptable properties to pick a unique benefit allocation. Later, we revisit this idea in our proposed methods.

Apart from the aforementioned fundamental properties that pertain to the economic side of the problem, computational tractability is also a practical concern, considering that we may need the complete list of coalition values $v(\mathscr{C})$ for all $\mathscr{C} \subseteq \mathscr{A}$ to fully describe the core and the least-core. For the coalitional games arising from the preemptive model, each coalition value requires another solution to MILP in (4), which is NP-hard in general. Hence, our goal is to find a core or a least-core benefit allocation that can be computed with limited queries to the coalitional value function. Next, we briefly review two benefit allocation mechanisms that are widely used in the literature.

### 4.1. Shapley value

The benefit assigned by the Shapley value is given by $\beta_a^{\text{Shapley}}(v) = \sum_{\mathscr{C}\subseteq\mathscr{A}} \frac{(|\mathscr{C}|-1)!(|\mathscr{A}|-|\mathscr{C}|)!}{|\mathscr{A}|!}(v(\mathscr{C}) - v(\mathscr{C}\setminus a))$. This benefit is the average of the marginal contribution of the area $a$ under all coalitions, considering also all possible orderings of areas. The Shapley value results in an efficient benefit allocation. Individual rationality is also satisfied if the coalitional value function is nondecreasing, since the marginal contributions would be nonnegative. On the other hand, the Shapley value is guaranteed to lie in the core only when the coalitional value function is supermodular. This is a restrictive condition that is not applicable to our problem. In addition, when the core is empty, the Shapley value does not necessarily lie in the least-core, making it incompatible with the fundamental properties we desire [53]. In terms of the computational performance, the calculation of the Shapley value requires the exhaustive enumeration of coalition values $v(\mathscr{C})$ for all $\mathscr{C} \subseteq \mathscr{A}$. Finally, it should be noted that the Shapley value is the unique efficient benefit allocation that satisfies dummy player, symmetry, and additivity properties simultaneously. Dummy player property requires $\beta_a = 0$ for all $a$ for which $v(\mathscr{C}) - v(\mathscr{C}\setminus a) = 0$ for all $\mathscr{C} \subseteq \mathscr{A}$. In other words, an area incapable of contributing to any coalition $\mathscr{C}$ ends up with zero benefits. Next, we show the relation between the previously discussed properties and the dummy player property.

**Proposition 1.** *(i) if $a'$ satisfies $v(\mathscr{A}) - v(\mathscr{A}\setminus a') = 0$, then $K_{\text{Core}}(v) \subset \{\beta \mid \beta_{a'} = 0\}$, (ii) if $a'$ satisfies $v(\mathscr{C}) - v(\mathscr{C}\setminus a') = 0$ for all $\mathscr{C} \subseteq \mathscr{A}$, then $K_{\text{Core}}(v,\epsilon^*(v)) \subset \{\beta \mid \beta_{a'} = 0\}$.*

[8] In coalitional games, efficiency is also often referred to as budget balance. For clarity, we use efficiency for the benefit allocation, and the term budget balance is reserved for the cost allocation.

[9] Supermodularity is attained if for any set the participation of an area results in a larger value increment when compared to the subsets of the set under consideration, i.e., $v(\mathscr{C} \cup \{a\}) - v(\mathscr{C}) \geq v(\mathscr{C}' \cup \{a\}) - v(\mathscr{C}')$, $\forall a \notin \mathscr{C}, \mathscr{C}' \subset \mathscr{C} \subseteq \mathscr{A}$.

This proposition provides a missing link in the comparisons of the Shapley value, the core, and the least-core in a generic coalitional game. This result shows that the core attains a more restrictive version of the dummy player property, i.e., an area incapable of contributing to the set $\mathscr{A}$ ends up with zero benefits. Finally, the least-core attains the dummy player property in the same way that it is defined for the Shapley value. The proof and the discussions on symmetry and additivity are relegated to Appendix E.

### 4.2. Nucleolus allocation

Among all efficient benefit allocations, the nucleolus allocation is the unique benefit allocation that minimizes the excesses of all coalitions in a lexicographic manner [70]. Nucleolus allocation lies in the least-core and hence attains the desirable economic properties. In terms of practical implementation, the lexicographic minimization is computationally demanding in the general case. Nucleolus allocation can be computed by solving a sequence of $\mathscr{O}(|\mathscr{A}|)$ linear programs with constraint sets that are parametrized versions of the core $K_{\text{Core}}(v)$, see [34,47]. However, each linear program requires the complete list of coalition values. In case the coalition values are given implicitly by the objective value of a single linear optimization problem with constraints depending on the participants of the coalition, the work by Hallefjord et al. [36] proposes using constraint generation algorithms. In this approach, $\mathscr{O}(|\mathscr{A}|)$ linear programs are solved by $\mathscr{O}(|\mathscr{A}|)$ constraint generation algorithms that iteratively generates coalitional values on demand. Nevertheless, we may still need to generate all possible coalition values [36,46]. When the number of areas is large, this approach involving the execution of the constraint generation algorithm $\mathscr{O}(|\mathscr{A}|)$ times becomes computationally prohibitive for our application. For the sake of completeness, Appendix F provides the mathematical definition for the nucleolus allocation and its comparison with the Shapley value.

## 5. Benefit allocation mechanisms for preemptive transmission allocation

In this section, the first benefit allocation mechanism, which is an ex-ante process with respect to the uncertainty realization, employs as coalitional value function the expected cost reduction. The second mechanism is an ex-post process that can be applied only when the scenario is unveiled, since it uses as coalitional value function the scenario-specific cost variation.

### 5.1. Benefit allocations for expected cost reduction

For the ex-ante allocation mechanism, the coalitional value function $\bar{v}(\mathscr{C}) = J(\emptyset) - J(\mathscr{C}) \geq 0$ for all $\mathscr{C} \subseteq \mathscr{A}$ is nondecreasing, since $J$ is nonincreasing. Given the function $\bar{v}$, an efficient benefit allocation, $\sum_{a\in\mathscr{A}} \beta_a(\bar{v}) = \bar{v}(\mathscr{A})$, would result in a cost allocation that is budget balanced in expectation, since $J(\mathscr{A}) = J(\emptyset) - \bar{v}(\mathscr{A}) = \mathbb{E}_s\big[\sum_{a\in\mathscr{A}} J_a^s(\emptyset)\big] - \sum_{a\in\mathscr{A}} \beta_a(\bar{v}) = \mathbb{E}_s\big[\sum_{a\in\mathscr{A}} J_a^s(\mathscr{A})\big]$. While designing a benefit allocation mechanism, our goal is to achieve the three fundamental properties, i.e., efficiency, individual rationality and stability, associated with the core $K_{\text{Core}}(\bar{v})$. However, as already mentioned, the previous results on the nonemptiness of the core are not applicable to our problem. The following condition is applicable to some specialized instances of $\bar{v}$ above.

**Proposition 2.** *$K_{\text{Core}}(\bar{v})$ is nonempty if there exists an area $a' \in \mathscr{A}$ such that $\bar{v}(\mathscr{A} \setminus a') = 0$.*

The proof is relegated to Appendix G. Note that this condition can only be attained in specialized instances of the preemptive model. For instance, in the case of a star graph $(\mathscr{A}, \mathscr{E})$, the central area would satisfy this condition, since it is indispensable for enabling any reserve exchange. However, in a general graph, the core could potentially be empty and we focus on this case in the illustrative example provided in Section 6.1.3. In case of an empty core, our goal is to achieve a least-core solution, which can be perceived as the second best outcome in our context. Other than approximating the stability property, the least-core also approximates the individual rationality property by relaxing the inequality constraints for singleton sets, i.e., $\beta_a \geq \bar{v}(a) - \epsilon^*(\bar{v}) = -\epsilon^*(\bar{v})$ for all $a \in \mathscr{A}$. The following proposition shows that the least-core is individually rational for $\bar{v}$.

**Proposition 3.** *$K_{\text{Core}}(\bar{v}, \epsilon^*(\bar{v}))$ lies in $\mathbb{R}_+^{\mathscr{A}}$.*

The proof is relegated to Appendix H. It relies on the observation that whenever the coalitional value function is given by a stochastic bilevel program any least-core allocation violating the individual rationality would imply the existence of an $\epsilon < \epsilon^*$, such that $K_{\text{Core}}(\bar{v}, \epsilon)$ is nonempty, contradicting the definition of the least-core. Thus, we can use the least-core to achieve efficiency, individual rationality and approximate stability, whenever the core is empty.

For this coalitional game, the Shapley value satisfies efficiency and individual rationality, but stability (or approximate stability) and computational tractability are not attained. We provide an example for stability violation in Section 6.1.1. The nucleolus allocation, on the other hand, lies in the least-core and it satisfies efficiency, individual rationality and approximate stability (but with no tractability). Based on these discussions, we propose a least-core selecting mechanism:

$$\underset{\epsilon,\,\beta}{\text{minimize}}\ \epsilon \quad \text{subject to}\ \epsilon \geq 0,\ \ \beta \in K_{\text{Core}}(\bar{v}, \epsilon). \tag{5}$$

Let $\hat{\epsilon}$ denote the optimal value of $\epsilon$ for this problem. If the core is empty, we have $\hat{\epsilon} = \epsilon^*(\bar{v}) > 0$ and problem (5) finds a least-core allocation. On the other hand, if the core is nonempty, we have $\hat{\epsilon} = 0$ and problem (5) finds instead a core benefit allocation, which attains properties of efficiency, individual rationality and stability. The nucleolus allocation always forms an optimal solution pair with $\hat{\epsilon}$ to problem (5), since it lies in the least-core. In fact, there are in general many optimal solutions to this problem. To this end, we will propose an additional criterion for tie-breaking.

Let $\beta^{\text{c}}$ be a desirable and a fair benefit allocation that is easy to compute but not necessarily in the core or in the least-core. An example could be the marginal contribution of each area $\beta^{\text{m}}$ : $\beta_a^{\text{m}} = \bar{v}(\mathscr{A}) - \bar{v}(\mathscr{A} \setminus a)$ for all $a \in \mathscr{A}$ which requires $|\mathscr{A}| + 2$ calls to problem (4). Receiving the marginal contribution can be regarded as a fair outcome.[10] This allocation satisfies individual rationality, dummy player and symmetry properties. However, it is generally not efficient, see Krishna [48], and not stable, see Karaca and Kamgarpour [43]. Another example could be $\beta^{\text{eq}} = (\bar{v}(\mathscr{A})/|\mathscr{A}|)\mathbf{1}^\top$ which assigns equal importance to each area. This choice requires two calls to problem (4) and it satisfies efficiency and individual rationality. However, this allocation also violates stability.

Starting from such a desirable benefit allocation, we can solve the following problem

$$\underset{\beta}{\text{minimize}}\ ||\beta - \beta^{\text{c}}||_2^2 \quad \text{subject to}\ \beta \in K_{\text{Core}}(\bar{v}, \hat{\epsilon}), \tag{6}$$

to obtain a unique benefit allocation for problem (5). The uniqueness follows from having a strictly convex objective. Let $\hat{\beta}(\bar{v}, \beta^{\text{c}})$ denote the optimal value of $\beta$ in problem (6). We define the benefit allocation $\hat{\beta}(\bar{v}, \beta^{\text{c}})$ as the *least-core selecting mechanism*. This

[10] This allocation coincides with the Vickrey-Clarke-Groves mechanism [48]. In an auction, this allocation ensures that truthfully reporting the preferences is a dominant strategy Nash equilibrium.

allocation achieves economic properties of the least-core, and also the core if the core is nonempty, while approximating an additional criterion defined by $\beta^{\mathrm{c}}$. For instance, if the marginal contribution $\beta^{\mathrm{m}}$ is chosen, problem (6) would pick the allocation $\hat{\beta}(\bar{v}, \beta^{\mathrm{m}})$ approximating the fairness of the marginal contribution.

Characterizing the constraint sets of problems (5) and (6) still requires exponentially many solutions to (4). We show that (5) and (6) can be solved by a single constraint generation algorithm, achieving computational tractability. As we discussed in the introduction, this formulation and its convergence are novel to our work. Previous works analyzed it only for computing an outcome from the core. Since the main goal of our paper is to provide techno-economic insights, we relegated these derivations to Appendix I.

### *5.2. Benefit allocations per scenario*

Allocating benefits for the expected cost reduction does not guarantee that the resulting cost allocation satisfies budget balance in every scenario. Having a surplus or a deficit might be undesirable, since this may necessitate a large financial reserve to buffer the fluctuations. To address this issue, here we focus on the allocation of the the scenario-specific cost variation, $J^s(\emptyset) - J^s(\mathscr{A})$. The coalitional value function in this case is given by $v^s(\mathscr{C}) = J^s(\emptyset) - J^s(\mathscr{C})$, for all $\mathscr{C} \subset \mathscr{A}$. Observe that the set function $v^s$ is not necessarily nondecreasing, while it can also map to negative reals, since the preemptive transmission allocation model does not guarantee that $J^s(\mathscr{C}) \leq J^s(\emptyset)$ holds. Given the function $v^s$, an efficient benefit allocation mechanism, $\sum_{a\in\mathscr{A}} \beta_a(v^s) = v^s(\mathscr{A})$, would result in a cost allocation that is budget balanced in scenario $s$, since $J^s(\mathscr{A}) = J^s(\emptyset) - v^s(\mathscr{A}) = \sum_{a\in\mathscr{A}} J^s_a(\emptyset) - \sum_{a\in\mathscr{A}} \beta_a(v^s) = \sum_{a\in\mathscr{A}} J^s_a(\mathscr{A})$.

Aiming at establishing a per-scenario benefit allocation, our goal now is to achieve the properties of the scenario-specific core $K_{\mathrm{Core}}(v^s)$. However, neither the previous results nor Proposition 2 apply to this core definition to prove that it is nonempty as it can be affirmed by the following result.

**Proposition 4.** *$K_{\mathrm{Core}}(v^s)$ is empty if there exists $\mathscr{C} \subset \mathscr{A}$ such that $v^s(\mathscr{A}) < v^s(\mathscr{C})$.*

The proof is relegated to Appendix K and to the best of our knowledge, it was not studied before. In practice, the condition would prevent the formation of the grand coalition $\mathscr{A}$, as shown in the example of Section 6.1.1. The coalition value $v^s(\mathscr{A})$ being negative is a special case of Proposition 4, since we would then have $v^s(\mathscr{A}) < v^s(a) = 0$ for all $a \in \mathscr{A}$. We see that it may not be realistic to achieve all three fundamental properties, and we should instead aim for the least-core $K_{\mathrm{Core}}(v^s, \epsilon^*(v^s))$. Note that in this case Proposition 3 is not applicable and the least-core would instead achieve efficiency, approximate individual rationality, and approximate stability.

For the coalitional game arising from the function $v^s$, the Shapley value satisfies efficiency, but individual rationality, stability, and computational tractability are not attained. On the other hand, the nucleolus allocation provides a least-core allocation. Note that, in contrast to the expected coalitional value function $\bar{v}$, the function $v^s$ is not implicitly given by an optimization problem. Instead, it is an ex-post calculation from the sequential electricity market after the uncertainty realization. As a result, the value function $v^s$ is not amenable to a constraint generation approach. Thus, we look at an alternative approach that can be computed in a computationally tractable manner. This approach will extend our results from Section 5.1, showing that any efficient benefit allocation for the expected cost reduction gives rise to an efficient scenario-specific benefit allocation that results in budget balance in every scenario.

Let $\beta(\bar{v}) \in \mathbb{R}^{\mathscr{A}}_{+}$ be an efficient individually rational benefit allocation for the expected cost reduction, computed prior to the uncertainty realization. We then define the following scenario-specific benefit allocation, $\beta(v^s, \beta(\bar{v})) \in \mathbb{R}^{\mathscr{A}}$, $\beta_a(v^s, \beta(\bar{v})) = \frac{\beta_a(\bar{v})}{\bar{v}(\mathscr{A})} v^s(\mathscr{A}), \quad \forall a \in \mathscr{A}$. The benefit $\beta_a(v^s, \beta(\bar{v}))$ for each area $a$ is computed based on an ex-post computation of $v^s(\mathscr{A})$ for the specific uncertainty realization $s$. Given $\beta(\bar{v})$, this definition does not require any further solutions to the preemptive transmission allocation model or the sequential market. The term $\beta_a(\bar{v})/\bar{v}(\mathscr{A}) \in [0, 1]$ can be considered as a percentage share of profits/losses depending on the sign of $v^s(\mathscr{A})$. (This also holds for any other weighting from the $|\mathscr{A}|$-simplex.) Notice that since $\sum_{a\in\mathscr{A}} \beta_a(v^s, \beta(\bar{v})) = v^s(\mathscr{A})$, the efficiency property holds. Moreover, having $\mathbb{E}[\beta_a(v^s, \beta(\bar{v}))] = \beta_a(\bar{v})$ implies that the scenario-specific benefit allocation $\beta(v^s, \beta(\bar{v}))$ satisfies in expectation the other fundamental properties of the original benefit allocation $\beta(\bar{v})$.

Given the above reasoning, we propose a *scenario-specific least-core selecting mechanism*, which builds upon the least-core selecting benefit allocation mechanism from problems (5) and (6) to define $\beta(v^s, \hat{\beta}(\bar{v}, \beta^{\mathrm{c}})) \in \mathbb{R}^{\mathscr{A}}$ according to the procedure above. We have previously showed that the allocation $\hat{\beta}(\bar{v}, \beta^{\mathrm{c}})$ satisfies individual rationality and approximate stability, while enabling a tractable computation via a constraint generation algorithm. In a similar vein, the scenario-specific version $\beta(v^s, \hat{\beta}(\bar{v}, \beta^{\mathrm{c}}))$ satisfies individual rationality and approximate stability in expectation, while still enabling a tractable computation. We illustrate this approach in Section 6. As a remark, it is possible to use the Shapley value and the nucleolus allocation in a similar manner. The comparisons of these mechanisms in the previous section would remain unchanged. A discussion on risk considerations and a method to handle out-of-sample computations are provided in Appendix L.

## 6. Numerical case studies

### *6.1. Illustrative three-area examples*

We describe a base model, which will be subject to several modifications in the system configuration and penetration of stochastic renewables to discuss the resulting changes in the benefit allocations described in Sections 4 and 5. We consider the nine-bus system depicted in Fig. 3 which comprises three areas. The intra-area transmission network consists of AC lines with capacity and reactance equal to 100 MW and 0.13 p.u., respectively. The four tie lines between areas 1 and 2, and between areas 2 and 3 are AC lines with capacity of 20 MW, and reactance of 0.13 p.u. each.

The day-ahead price offers and the generation capacities of conventional units are provided in Appendix M. Units $i_1$, $i_4$, and $i_7$ are inflexible, i.e., these units cannot change their generation level during real-time operation, while all remaining units are flexible offering half of their capacity for upward and downward reserves provision at a cost equal to 10% of their day-ahead energy offer $C$. The cost of load shedding $C^{\mathrm{sh}}$ is equal to 1000€ /MWh for the inelastic electricity demands $D_3 = 220$ MW, $D_6 = 190$ MW, and $D_9 = 220$ MW. In addition, there are three wind power plants, $j_3$, $j_6$, and $j_9$, with installed capacities 50, 80, and 50 MW, respectively. The stochastic wind power is modeled using two scenarios, $s_1$ and $s_2$, listed in Appendix M with probability of occurrence 0.6 and 0.4, respectively. The expected wind power production $\overline{W}_j$ for $j_3$ is equal to 42 MW, for $j_6$ is equal to 70.4 MW, and for $j_9$ is equal to 42 MW. Wind power price offers and subsequently the wind power spillage costs are considered to be zero. Following the prevailing approach in which regional capacity markets are cleared separately, we set the percentage of transmission capacity allocated to reserves equal to $\chi = 0$. Reserve requirements are listed in Appendix M.

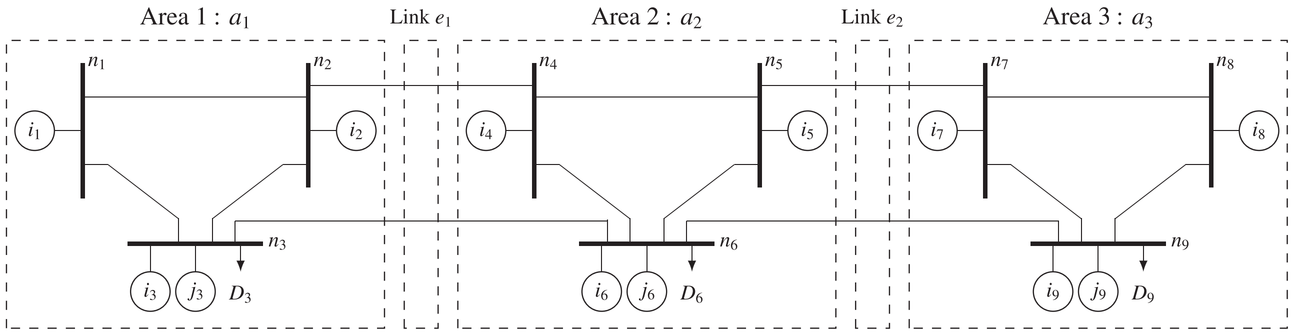


**Fig. 3.** Nine-node three-area interconnected power system.

**Table 1**
Comparison of market costs (in €).

| Model | Existing Seq. Market | Preemptive Model |
|---|---|---|
| $[\chi_{e_1},\ \chi_{e_2}]$ | [0, 0] | [0, 0.0592] |
| Reserve capacity cost | 194.0 | 191.6 |
| Day-ahead cost | 13,087.2 | 13,120.2 |
| Balancing cost in $s_1$ | 1,150.0 | −410.7 |
| Balancing cost in $s_2$ | 9,750.0 | 431.5 |
| Total cost in $s_1$ | 14,431.2 | 12,901.2 |
| Total cost in $s_2$ | 23,031.2 | 13,743.4 |

**Table 2**
Cost allocation for each area in the existing sequential market (in €).

| Areas | Area 1 | Area 2 | Area 3 |
|---|---|---|---|
| $J_a^{s_1}(\emptyset)$ | 4,348.4 | 9,853.8 | 229.0 |
| $J_a^{s_2}(\emptyset)$ | 16,348.4 | 3,453.8 | 3,229.0 |

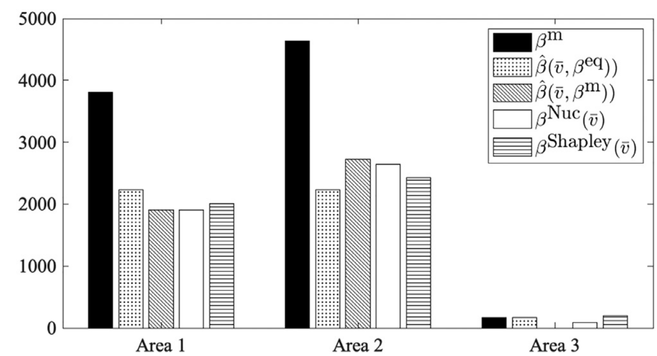


**Fig. 4.** Benefit allocations for the three-area system (in €).

The market costs and transmission allocations resulting from the preemptive model are provided in Table 1. The preemptive model reallocated transmission resources from the day-ahead energy trading to the reserve capacity trading, increasing the costs in the day-ahead market. This reallocation yields an expected system cost of 13,238.0€, which translates to 25.9% reduction compared to the cost of 17,871.2€ from the existing sequential market. Under the existing setup with $\chi = 0$, the uncertainty realization $s_2$ leads to significant load shedding in the balancing stage. In this scenario, even though we have enough reserve capacity, we are not able to deploy it due to network congestion. This problem is avoided by enabling reserve exchange when the preemptive model is implemented. Quantities assigned to each generator at all trading floors are provided in Appendix N.

We now provide a budget balanced cost allocation method for the existing sequential market. For this method, we assume that all three trading floors are cleared by marginal pricing mechanisms (zonal prices for the reserve capacities, nodal prices for the day-ahead and balancing energy services), albeit, similar methods can be applied also to other payment mechanisms. This method assigns producer and consumer surpluses, and congestion rents of the intra-area lines to their corresponding areas, and divides the congestion rents of the tie lines equally between the adjacent areas, see [49]. Budget balance holds since the market cost is given by the opposite of the sum of producer and consumer surpluses, and congestion rent for each trading floor. These values are summarized in Appendix N. We refer to Table 2 for the resulting cost allocations. Area 1 is allocated a large cost in scenario $s_2$ because of the load shedding in node 3.

*6.1.1. Comparison of the different benefit allocations*

Benefit allocation mechanisms for the expected cost reduction are provided in Fig. 4. The core is nonempty since area 2 satisfies the veto condition in Proposition 2. Marginal contribution benefit allocation $\beta^{\text{m}}$ is not in the core since it is not efficient. We provide this allocation since it can be regarded as a fair outcome. Observe that the marginal contributions of areas 1 and 2 are larger than that of area 3. This is because area 1 has low cost generators and area 2 is indispensable for any coordination considering that in the current network configuration, in which areas 1 and 3 are not directly interconnected, area 2 has to act as an intermediary for any reserves exchange.

The Shapley value $\beta^{\text{Shapley}}$ is not in the core. Among the core constraints, combining $\sum_{a\in\mathscr{A}} \beta_a = v(\mathscr{A})$ with $\sum_{a\in\mathscr{A}\setminus\hat{a}} \beta_a \geq v(\mathscr{A}\setminus\hat{a})$ implies that $\beta_{\hat{a}} \leq \beta^{\text{m}}_{\hat{a}} = v(\mathscr{A}) - v(\mathscr{A}\setminus\hat{a})$, or equivalently, no area can receive more than its marginal contribution in the core. This condition is violated for the Shapley value assigned to area 3. The coalitional value function is also not supermodular, since $\bar{v}(\{1,2,3\}) - \bar{v}(\{1,2\}) \not\geq \bar{v}(\{2,3\}) - \bar{v}(\{2\}) \Rightarrow 4{,}633.1 - 4{,}460.5 \not\geq 826.8 - 0$. On the other hand, the nucleolus $\beta^{\text{Nuc}}$ is in the core, however, the lexicographic minimization results in allocating benefits to area 3. We later see that there is a core allocation that better approximates the marginal contribution in terms of minimizing the Euclidean distance by allocating no benefits to area 3.

Finally, we employ our approach approximating two different criteria, i.e., marginal contribution and equal shares, with corresponding allocations being denoted as $\hat{\beta}(\bar{v}, \beta^{\text{m}})$ and $\hat{\beta}(\bar{v}, \beta^{\text{eq}})$, respectively. These two outcomes are different from each other, and they approximate their respective fairness consideration in an effective manner. This criterion should be decided either by the regulator or it should be based on the consensus of participating areas. In the following, we will approximate the marginal contribution, since similar discussions can be made for any other criteria.

Next, we study the budget balance per scenario for the cost allocation in the preemptive model. For all efficient benefit allocations of the expected cost reduction, i.e., all methods except the marginal contribution allocation, the budget

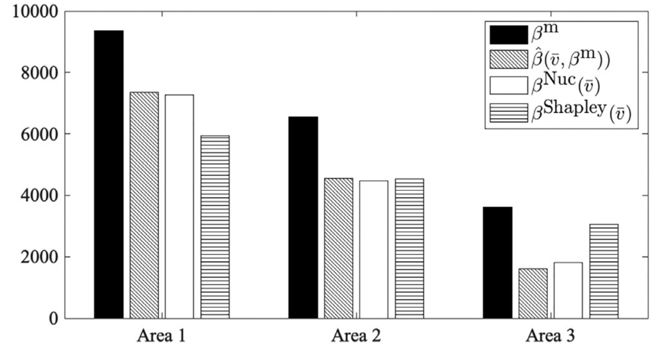


**Fig. 5.** Benefit allocations after connecting areas 1 and 3 (in €).

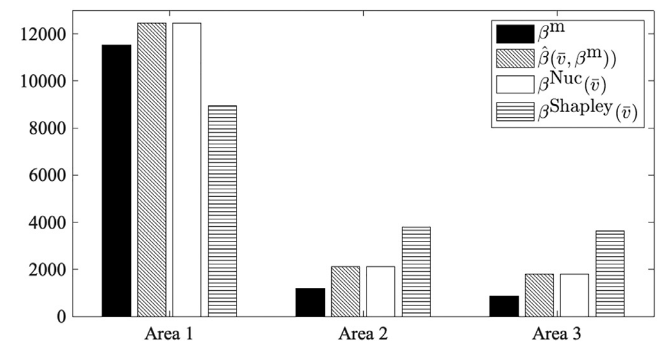


**Fig. 6.** Benefit allocations in case the core is empty (in €).

$\sum_{a\in\mathscr{A}} J_a^s(\mathscr{A}) - J^s(\mathscr{A})$ remains unchanged. In scenario $s_1$, there is a deficit of 3,103.1€, whereas in scenario $s_2$ there is a surplus of 4,654.7€, thus budget balance is obtained in expectation. In the coalitional game arising from the scenario-specific cost variation, despite that $K_{\mathrm{Core}}(\bar{v})$ is nonempty, the core $K_{\mathrm{Core}}(v^{s_1})$ is empty, since the condition in Proposition 4 is satisfied by $v^{s_1}(\{1,2\}) = J^{s_1}(\emptyset) - J^{s_1}(\{1,2\}) > J^{s_1}(\emptyset) - J^{s_1}(\{1,2,3\}) = v^{s_1}(\{1,2,3\}) \Rightarrow 14{,}431.2 - 12{,}884.6 > 14{,}431.2 - 12{,}901.2$. For scenario $s_2$, this condition is not satisfied and $K_{\mathrm{Core}}(v^{s_2})$ is nonempty, since the coalitional game is supermodular.

To address the budget balance, we now employ the proposed scenario-specific least-core selecting mechanism. The scenario-specific allocations generated by $\hat{\beta}(\bar{v}, \beta^{\mathrm{m}})$ for the expected cost reduction are given by $\beta(v^{s_1}, \hat{\beta}(\bar{v}, \beta^{\mathrm{m}})) = [628.5,\ 901.5,\ 0]^\top$ and $\beta(v^{s_2}, \hat{\beta}(\bar{v}, \beta^{\mathrm{m}})) = [3{,}815.2,\ 5{,}472.6,\ 0]^\top$. These allocations result in a budget balanced cost allocation under both scenarios, since they sum up to the scenario-specific cost variations in Table 1. In Appendix O, we provide an out-of-sample example. In the remainder, we focus our efforts on the game arising from the expected cost reduction, since we can always map the benefit allocations to the scenario-specific case using our proposed approach.

In our numerics, all problems are solved with GUROBI 7.5 called through MATLAB on a computer equipped with 32 GB RAM and a 4.0 GHz Intel i7 processor. The computational comparison for the three benefit allocation mechanisms for the expected cost reduction can be summarized as follows. The Shapley value is computed in 39.6 seconds, whereas the nucleolus is computed in 41.3 seconds. On the other hand, the least-core allocations for marginal contribution and equal shares are computed in 6.3 and 6.7 seconds, respectively. Following our previous discussions, the computation time difference between our methods and the others will be even more significant when there are more areas. Because of this reason, the computational methods will be studied and discussed in detail for the larger realistic case study.

#### *6.1.2. Impact of the uncertainties on benefit allocations*

Here, we aim to assess the impact of the spatial correlation of the wind power forecast errors on the outcome of the different benefit allocation mechanisms that we consider in this work. In order to eliminate the impact of the network topology (cf. Appendix P), we connect areas 1 and 3 via two AC lines. The first connects nodes 1 and 8, and the second connects nodes 3 and 9, each with transmission capacity of 20 MW, and reactance of 0.13 p.u. The area graph is not a star anymore, and Proposition 2 is not applicable. However, we verified that the core is still nonempty.

The resulting benefit allocations for the expected cost reduction are provided in Fig. 5, which shows that areas 1 and 2 receive most of the benefit under every allocation mechanism. This outcome can be explained considering that these areas have complementary wind power production scenarios, i.e., the corresponding wind power scenarios exhibit negative correlation. Moreover, area 1 has low cost generation. Finally, notice that the total benefits are greater than the ones from the example in Section 6.1.1. This follows since compared to Section 6.1.1 expected system cost is increased by 49% (26,687.9€) in the existing sequential market due to additional network dependencies, whereas this cost is decreased by 0.01% (13,161.0€) in the preemptive model.

#### *6.1.3. Benefit allocations in the case of an empty core*

A natural question that arises in the context of this work is how the different benefit allocation mechanisms perform when we have an empty core, which can occur when the condition in Proposition 2 is not satisfied. To this end, we modify the example in Section 6.1.2 by changing the wind scenarios. The stochastic wind power generation is modeled using two scenarios, $s_1$ and $s_2$ with probability of occurance 0.8 and 0.2. We have 1 and 0.8 for $j_3$, 0.4 and 1 for $j_6$, 0.4 and 1 for $j_9$ as the percentages of the nominal values of the plants, respectively. Hence, the corresponding expected wind power productions for $j_3$ is equal to 48 MW, for $j_6$ is equal to 41.6 MW, and for $j_9$ is equal to 26 MW. The reserve requirements are recomputed accordingly. Since the uncertainty is significantly increased, we allow the units $i_1$, $i_4$, and $i_7$ to be flexible in order to ensure feasibility.

The resulting benefit allocations for the expected cost reduction are provided in Fig. 6. We observe that the nucleolus and the least-core selecting benefit allocation coincide. For both allocations, the maximum violation of a stability constraint is given by $\epsilon^* = 924.9€$, where $\epsilon^*(\bar{v}) = \min\{\epsilon \mid K_{\mathrm{Core}}(\bar{v}, \epsilon) \neq \emptyset\}$. On the other hand, the maximum stability violation for the Shapley value is 2,752.0€. In other words, if the Shapley value is utilized, there are 3 times the profits to be made by not participating in the preemptive model compared to the case implementing a least-core allocation. We see that all benefit allocation mechanisms allocated the most benefits to area 1, since it has low cost generation and also its wind profile complements the wind profiles of areas 2 and 3.

### *6.2. Case study based on the IEEE RTS*

We now consider a six-area power system that is based on the modernized version of the IEEE Reliability Test System (RTS) presented in Pandzic et al. [63]. The definitions of the areas corre-

**Table 3**
Comparison of market costs (in €).

| Model | Existing Seq. Market | Preemptive Model |
|---|---|---|
| $\chi = [\chi_{e_1}, \ldots, \chi_{e_7}]$ | [0, 0, 0, 0, 0, 0, 0] | [0, 0.359, 0, 0.038, 0, 0, 0] |
| Reserve capacity cost | 2,392.5 | 2,389.4 |
| Day-ahead cost | 90,734.2 | 90,733.3 |
| Expected balancing cost | −3,430.3 | −5,527.9 |
| Expected cost | 89,696.4 | 87,594.8 |

**Table 4**
Expected cost allocation for each area in the existing sequential market (in €).

| Areas | Area 1 | Area 2 | Area 3 | Area 4 | Area 5 | Area 6 |
|---|---|---|---|---|---|---|
| $\mathbb{E}_s[J_a^s(\emptyset)]$ | 8,966.1 | 25,252.6 | 10,085.2 | 10,208.2 | 25,151.1 | 10,033.2 |

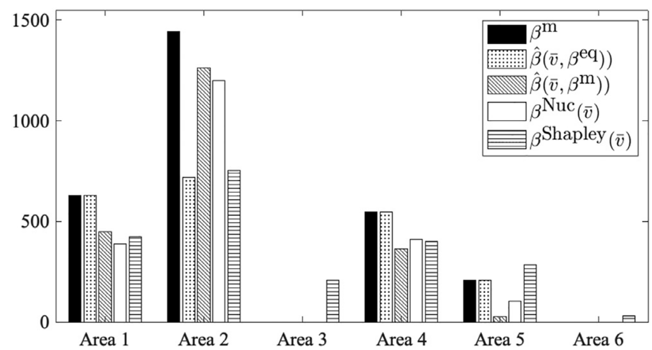


**Fig. 7.** Benefit allocations for the IEEE RTS case study (in €).

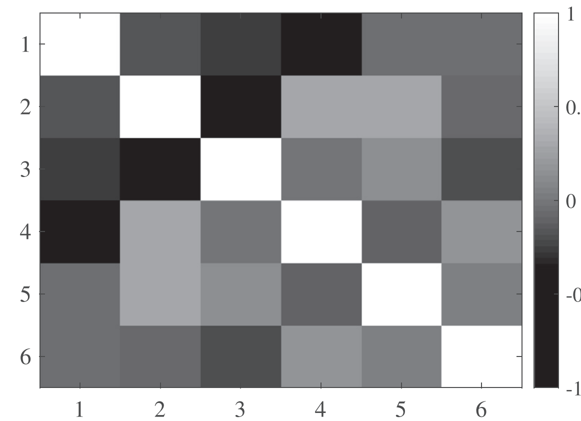


**Fig. 8.** The Pearson correlation coefficients for the wind profiles of all areas.

spond to the ones proposed by Dvorkin et al. [22] and Jensen et al. [40], and they are provided in Appendix Q. The nodal positions, types, generation capacities and offers from conventional and wind power generators, and transmission line parameters are provided in Karaca et al. [41]. Due to their limited flexibility, nuclear, coal and integrated gasification combined cycle (IGCC) units do not provide any reserves. On the other hand, open and combined cycle gas turbines (OCGT and CCGT) offer 50% of their capacity for upward and downward reserves at a cost equal to 20% of their day-ahead energy offer. Wind power production is modeled using a set of 10 equiprobable scenarios obtained from Bukhsh [13]. This scenario set is originally generated according to the methodology explained in Papaefthymiou and Pinson [64], and it captures the spatial correlation of forecast errors over the different wind farm locations, see also Fig. 8 and Karaca et al. [41]. In our case study, areas 2, 4, and 5 are assumed to be close to each other, and hence the corresponding wind power production exhibits higher correlation. Evaluation of this aspect for different areas will be shown to be a useful predictor for the benefit allocation methods. The demand is inelastic with the cost of load shedding 1,000€ /MWh. In the existing sequential market, the percentage of transmission capacity allocated to reserves exchange is set to $\chi = 0$, while the reserve requirements are calculated according to the methodology discussed in Section 6.1.

Table 3 compares the costs and transmission allocations resulting from the existing market with $\chi = 0$ and the preemptive model where $\chi$ is a decision variable. The preemptive model yields an expected cost of 87,594.8€, which translates to 2.3% reduction compared to 89,696.4€ from the existing market. This can be explained by 2,097.6€ reduction in the expected balancing cost obtained by eliminating load shedding. Using the approach in Section 6.1, we provide the expected values for a budget balanced cost allocation for the existing sequential market in Table 4.

The results of the different benefit allocation mechanisms for the expected cost reduction are provided in Fig. 7. We verified that the core is nonempty by finding a core allocation even though the condition in Proposition 2 is not satisfied. Marginal contribution benefit allocation is not in the core since it is not efficient, whereas the Shapley value is not in the core since areas 3, 5, and 6 receive more than their marginal contributions. The nucleolus and the least-core selecting benefit allocation mechanisms result in core allocations. Notice that our approach provides a different benefit allocation depending on the criteria considered. The nucleolus allocation is not consistent with the marginal contribution allocation since it allocates more benefits to area 4 compared to area 1. All mechanisms allocated the most benefits to area 2, since it has a central role by being well-connected in the area graph. On the other hand, areas 1 and 4 are also allocated a significant amount, since they are the two largest areas with wind profiles complementing each other as it is shown in Fig. 8.

We now provide a discussion on the computational comparison for the different benefit allocation mechanisms. The coalitions $J(\emptyset)$ and $J(\mathscr{A})$ are precomputed to obtain $v(\mathscr{A})$, in 19.4 and 35.4 seconds, respectively. The calculation of the marginal contribution allocation, which involves solving the preemptive model (4) for coalitions $\{\mathscr{A} \setminus \{a\}\}_{a\in\mathscr{A}}$, requires 119.7 seconds. The Shapley value requires solving the preemptive model (4) for all coalitions except the singleton sets, the empty set, and the full set, i.e., $2^6 - 6 - 1 - 1 = 58$ coalitions, and the resulting computational time is 1,264.6 seconds. The least-core selecting mechanism with the marginal contribution criteria requires only a single iteration from the constraint generation algorithm, which takes 84.8 seconds. This constraint generation algorithm converges fast, since in this case the algorithm starts with an initial family of coalitions ($\mathscr{F}^1$ in Appendix I) given by the coalitions that were used to compute the marginal contribution allocation. On the other hand, the least-core selecting mechanism with the equal shares criteria requires four iterations from the constraint generation algorithm, which takes 150.4 seconds. Notice that, in this case, the initial family of coalitions is empty. Finally, using the method proposed in Fromen [34], Kopelowitz [47], the nucleolus is computed by solving 15 linear programs sequentially to find 21 coalitional equality constraints that fully describe the nucleolus allocation. However, this method scales exponentially with the number of areas considered in the application, since it needs the complete list of coalition values. This computation takes 1,266.2 seconds. In Appendix R, we provide modifications to the IEEE RTS case study to evaluate impact of wind power penetration levels and available flexibility.[11]

[11] As an alternative, the iterative method in [36] would require running 15 separate constraint generation algorithms, increasing significantly the computational time compared to the least-core selecting mechanism, since each algorithm run requires at least one iteration of constraint generation.

## 7. Conclusion

As a summary of our methodological contributions, we first formulated a coalition-dependent preemptive transmission allocation model that defines the optimal inter-area transmission capacity allocation between energy and reserves for a given set of participating areas. We then accompanied this model with benefit allocation mechanisms such that all coalition members have sufficient benefits to accept the solution proposed. We formulated the coalitional game both as an ex-ante and as an ex-post process with respect to the uncertainty realization and we showed that the former results in budget balance in expectation, whereas the latter results in budget balance in every realization. Applying the prevailing benefit allocations to a larger case study, we showed that they are unable to find a benefit allocation with minimal stability violation within a reasonable computational timeframe. To address this issue for both coalitional games, we proposed the least-core selecting benefit allocation mechanism and we formulated an iterative constraint generation algorithm for its efficient computation. Considering that this work aims to contribute to the ongoing discussion towards the design of the transmission allocation model, our benefit allocation mechanism can be adapted to different plausible fairness criteria that may be imposed by the regulatory authorities, moving towards the full integration of the balancing markets.

Following the previous detailed discussions, it becomes clear that the European market regulators aim for the establishment of an integrated EU-wide reserve market, which will enable reserve exchanges across the European power system. However, since energy and reserve capacity markets are cleared separately, there is a need to pre-allocate the available transmission capacity between energy and reserve capacity auctions. Up to this date, the exact methodology for allocating inter-area transmission capacity to reserves is still subject to discussion and the final proposal will have to to be approved by the ENTSO-E members [32] [26, (14)]. Aiming to contribute to those ongoing regulatory and market design discussions, our work used a decision-support/analysis tool to set optimal transmission capacity allocations and based on it, proposed different benefit allocation mechanisms. Our analysis and studies provided valuable insights about the integration of European reserves market and highlighted the implications for the integration of reserve markets in terms of social welfare for each individual area.

We now summarize several important learnings from these studies in the following. First, we showed that transmission allocation between energy and reserve products can impact significantly the overall social welfare, and thus it is imperative to understand the techno-economic factors that drive the benefit allocations of each area, before splitting the available transmission capacity between the two markets. To provide further insights, we showed that the three major factors suggesting a larger benefit allocation are the amount of available flexible generation, connectivity level of the area in the network, and the negative correlation of uncertain generation with respect to the other areas. It should be noted that concurrently to this work, some TSOs are discussing different transmission allocation methodologies that can take advantage of day-ahead energy market and reserve market bid information [1]. Compared to these discussions, the preemptive model under study includes also information on the real-time balancing market. In contrast to our study, ACER [1] does not address the fair allocation of benefits. Instead, it explicitly suggests that if a method is implemented, by eighteen months after approval, all TSOs should publish an impact assessment including their estimated costs and benefits for their areas resulting from the transmission allocation and the reserve exchange. We believe that our proposed methodology and the discussions we provide in this work can provide early insights on the potential results of this impact assessment and will contribute to the ongoing discussions, until a final decision is reached by the regulators and TSOs.

There are definitely more challenges remaining to be answered to establish reserve exchanges in Europe. Major concern right now for the operators is the integration process itself (i.e., development of rules, processes, IT platforms). The European countries still have very different and separate ancillary services markets, imbalance pricing systems, and reserve procurement mechanisms. Nonetheless, it is becoming more and more clear that the issues of benefit allocation should be thoroughly studied in order to ensure the successful implementation of the integrated reserve market in the long term and ensure that all agents (TSOs) are treated fairly. For instance, Avramiotis-Falireas et al. [5] show that the issue of fair settlements is currently under investigation for the simpler setting of imbalance netting by the Swiss TSO - Swissgrid. In the same vein, the stakeholder document from the IGCC project IGCC [39, §6], developed by ten European TSOs, describes analytically a settlement scheme for the imbalance netting process that takes into account explicitly the aspect of fair distribution of the overall benefits for each IGCC member TSO, see also Contu et al. [15]. In this regard, our studies point out that a fair distribution of overall benefits is relevant also when we go beyond the simple imbalance netting to reserve exchanges in Europe.

Our future work on reserve exchanges will explore the development of decentralized schemes that enable the coordination of areas in terms of transmission allocations, while preserving privacy of the areas with minimal exchange of intra-area information. In the current setup of our approach, a single ('centrally obtained') scenario set is a prerequisite. However, going for a decentralized setup can enable us to study the case where each operator have different scenario sets. We believe that modelling TSO's imperfect information about the cross-border resources is an important additional element in order to assess both technical and regulatory considerations.

In terms of future work related to modelling, incorporating a non-convex lower level day-ahead market problem to the bilevel preemptive model could be valuable to understand the effect of complex block bids. We are also interested in including constraints on the amount of cross-border reserves that can be procured, e.g., X% of zonal reserve requirements should be procured from local resources, and study the impact of these constraints on our approach. Incorporating the potential congestion from zonal balancing market modelling approaches into the preemptive model would also be an interesting subject for further studies. Finally, as it was discussed in detail in Section 3.3, our ongoing work is focused on benefit redistribution mechanisms for individual market participants as an extension to the benefit allocation mechanisms for the areas including their operators and their market participants as a whole. We are currently studying side payments to ensure that, after a fair redistribution, the cost allocation of each area is close to what is suggested by the benefit allocation methods in this work.

### 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.

### CRediT authorship contribution statement

**Orcun Karaca:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Validation, Writing – original draft, Visualization. **Stefanos Delikaraoglou:** Conceptualization, Methodology, Formal analysis, Validation, Writing – original draft. **Gabriela Hug:** Conceptualization, Validation, Supervision, Funding acquisition. **Maryam Kamgarpour:** Conceptualization, Validation, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

## Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.omega.2022.102711. Appendices are provided in the supplementary material.

## References


[1] ACER. Methodology for a co-optimised allocation process of cross-zonal capacity for the exchange of balancing capacity or sharing of reserves in accordance with the commission regulation (EU) 2017/2195 of 23 November 2017. 2020.
[2] Agency for the Cooperation of Energy Regulators (ACER). Framework guidelines on electricity balancing. 2012.
[3] Ahlstrom M, Ela E, Riesz J, O'Sullivan J, Hobbs BF, O'Malley M, et al. The evolution of the market: designing a market for high levels of variable generation. IEEE Pow and En Mag 2015;13:60–6.
[4] Ahmadi-Khatir A, Conejo AJ, Cherkaoui R. Multi-area unit scheduling and reserve allocation under wind power uncertainty. IEEE Trans on Pow Syst 2013;29:1701–10.
[5] Avramiotis-Falireas I, Margelou S, Zima M. Investigations on a fair TSO-TSO settlement for the imbalance netting process in European power system. In: 15th Int. Conf. on the EEM. IEEE; 2018. p. 1–6.
[6] Baeyens E, Bitar EY, Khargonekar PP, Poolla K. Coalitional aggregation of wind power. IEEE Trans on Pow Syst 2013;28:3774–84.
[7] Baldick R.. Why doesn't the EU co-optimize the procurement of ancillary services with energy? 2017.
[8] Birge JR, Louveaux F. Introduction to stochastic programming. Springer Sci & B Med; 2011.
[9] Biskas PN, Chatzigiannis DI, Bakirtzis AG. European electricity market integration with mixed market designs–Part I: formulation. IEEE Trans Power Syst 2013;29:458–65.
[10] Bondy DEM, Tarnowski G, Heussen K, Hansen LH. Operational scenario: manual regulating power. Technical Report iPower Consortium; 2014.
[11] Bose S, Low SH. Some emerging challenges in electricity markets. In: Smart grid control. Springer; 2019. p. 29–45.
[12] Bouffard F, Galiana FD, Conejo AJ. Market-clearing with stochastic security-part i: formulation. IEEE Trans on Pow Syst 2005;20:1818–26.
[13] Bukhsh W.. Data for stochastic multiperiod optimal power flow problem. https://sites.google.com/site/datasmopf/home; 2017.
[14] Churkin A, Pozo D, Bialek J, Korgin N, Sauma E. Can cross-border transmission expansion lead to fair and stable cooperation? northeast asia case analysis. En Econ 2019:104498.
[15] Contu M, Allella F, Carlini EM, Montone S, Pascucci A, Michi L, Pecoraro G. The european electricity balancing platforms and the imbalance netting process: Terna's participation in the international grid control cooperation. In: AEIT Int. An. Conf.. IEEE; 2019. p. 1–6.
[16] Cory-Wright R, Philpott A, Zakeri G. Payment mechanisms for electricity markets with uncertain supply. Oper Res Letters 2018;46:116–21.
[17] Cramton P. Electricity market design. Ox Rev of Econ P 2017;33:589–612.
[18] CREG. Functioning and design of the Central West European day-ahead flow based market coupling for electricity: impact of TSOs discretionary actions, december 2017. Technical Report; 2017.
[19] Day RW, Raghavan S. Fair payments for efficient allocations in public sector combinatorial auctions. Management Sci 2007;53:1389–406.
[20] Delikaraoglou S, Pinson P. Optimal allocation of HVDC interconnections for exchange of energy and reserve capacity services. En Syst 2018:1–41.
[21] Domínguez R, Oggioni G, Smeers Y. Reserve procurement and flexibility services in power systems with high renewable capacity: effects of integration on different market designs. Int J of Elec Pow & En Syst 2019;113:1014–34.
[22] Dvorkin V, Delikaraoglou S, Morales JM. Setting reserve requirements to approximate the efficiency of the stochastic dispatch. IEEE Trans on Pow Syst 2018;34:1524–36.
[23] EC. Commission regulation (EU) 2017/2195 on establishing a guideline on electricity balancing, November 2017. 2015.
[24] EC. Integration of electricity balancing markets and regional procurement of balancing reserves, final report. 2016.
[25] EC. Commission Regulation (EU) 2017/2195 Establishing a guideline on electricity balancing. 2017.
[26] EC. Commission regulation 2019/943 on the internal market for electricity. 2019.
[27] EI NVE. Reduced capacity on German-Nordic interconnectors, regulatory framework and socioeconomic effects on the European electricity market, june 2017. Technical Report; 2017.
[28] Elia, 50Hertz, EGI. Future-proofing the EU energy system towards 2030, december 2019. 2019.
[29] Energinet.dk. Reservation of capacity of ancillary services - general principles and the sk4 case. http://www.elforsk.se/Documents/Market%20Design/seminars/Interconnectors/4Energinetdk.pdf; 2010.
[30] ENTSO-E. Network code on electricity balancing, august 2014. 2014.
[31] ENTSO-E. An overview of the european balancing market and electricity balancing guideline. 2018a.
[32] ENTSO-E. Commission regulation (EU) 2017/2195 - EB Deliverables. 2018b.
[33] Exizidis L, Kazempour J, Papakonstantinou A, Pinson P, De Greve Z, Vallee F. Incentive-compatibility in a two-stage stochastic electricity market with high wind power penetration. IEEE Trans on Pow Syst 2019;34:2846–58.
[34] Fromen B. Reducing the number of linear programs needed for solving the nucleolus problem of n-person game theory. Eur J of Oper Res 1997;98:626–36.
[35] Grimm V, Orlinskaya G, Schewe L, Schmidt M, Zöttl G. Optimal design of retailer-prosumer electricity tariffs using bilevel optimization. Omega (Westport) 2020. 102–327.
[36] Hallefjord A, Helming R, Jørnsten K. Computing the nucleolus when the characteristic function is given implicitly: a constraint generation approach. Int J of Game Th 1995;24:357–72.
[37] He W, Yang Y, Wang Z, Zhu J. Estimation and allocation of cost savings from collaborative CO2 abatement in China. En Econ 2018;72:62–74.
[38] Hobbs BF, Rijkers FA, Boots MG. The more cooperation, the more competition? a cournot analysis of the benefits of electric market coupling. The En J 2005:69–97.
[39] IGCC. Stakeholder document for the principles of IGCC. 2016.
[40] Jensen TV, Kazempour J, Pinson P. Cost-optimal ATCs in zonal electricity markets. IEEE Trans on Pow Syst 2017;33:3624–33.
[41] Karaca O., Delikaraoglou S., Hug G., Kamgarpour M.. System data—enabling inter-area reserves exchanges through stable benefit allocation mechanisms. doi:10.5281/zenodo.3579082; 2021.
[42] Karaca O, Delikaraoglou S, Kamgarpour M. A market-based approach for enabling inter-area reserve exchange. Oper Res Letters 2021;49:501–6.
[43] Karaca O, Kamgarpour M. Core-selecting mechanisms in electricity markets. IEEE Trans on Smart Grid 2020;11:2604–14.
[44] Karaca O, Sessa PG, Walton N, Kamgarpour M. Designing coalition-proof reverse auctions over continuous goods. IEEE Trans on Aut Contr 2019;64:4803–10.
[45] GmbH KEMA. Impact of a significant share of renewable energies on the European power generation system tec.rep: 9011-700. 2014.
[46] Kimms A, Çetiner D. Approximate nucleolus-based revenue sharing in airline alliances. Eur J of Oper Res 2012;220:510–21.
[47] Kopelowitz A. Computation of the kernels of simple games and the nucleolus of n-person games. Technical Report The Hebrew University of Jerusalem, Department of Math; 1967.
[48] Krishna V. Auction theory. Academic press; 2009.
[49] Kristiansen M, Muñoz FD, Oren S, Korpås M. A mechanism for allocating benefits and costs from transmission interconnections under cooperation: a case study of the north sea offshore grid. The En J 2018;39.
[50] Leuthold F, Jeske T, Weigt H, Von Hirschhausen C. When the wind blows over Europe: a simulation analysis and the impact of grid extensions. Available at SSRN 1328971 2009.
[51] Leuthold F, Weigt H, Von Hirschhausen C. Efficient pricing for European electricity networks–the theory of nodal pricing applied to feeding-in wind in Germany. UP 2008;16:284–91.
[52] Marien A, Luickx P, Tirez A, Woitrin D. Importance of design parameters on flowbased market coupling implementation. In: Int. Conf. on the EEM; 2013. p. 1–8.
[53] Maschler M, Peleg B, Shapley LS. Geometric properties of the kernel, nucleolus, and related solution concepts. Math of Oper Res 1979;4:303–38.
[54] Mitridati L, Kazempour J, Pinson P. Design and game-theoretic analysis of community-based market mechanisms in heat and electricity systems. Omega (Westport) 2019;99. 102–177.
[55] Morales JM, Conejo AJ, Liu K, Zhong J. Pricing electricity in pools with wind producers. IEEE Trans on Pow Syst 2012;27:1366–76.
[56] Morales JM, Conejo AJ, Pérez-Ruiz J. Economic valuation of reserves in power systems with high penetration of wind power. IEEE Trans on Pow Syst 2009;24:900–10.
[57] Morales JM, Zugno M, Pineda S, Pinson P. Electricity market clearing with improved scheduling of stochastic production. Eur J of Oper Res 2014;235:765–74.
[58] Nagayama D, Horita M. A network game analysis of strategic interactions in the international trade of Russian natural gas through Ukraine and Belarus. En Econ 2014;43:89–101.
[59] Neuhoff K. Large-scale deployment of renewables for electricity generation. Ox Rev of Econ P 2005;21:88–110.
[60] Newbery D, Strbac G, Viehoff I. The benefits of integrating european electricity markets. En Pol 2016;94:253–63.
[61] Owen G. On the core of linear production games. Math Prog 1975;9:358–70.
[62] Pan K, Guan Y. Integrated stochastic optimal self-scheduling for two-settlement electricity markets. INFORMS J Comput 2022.
[63] Pandzic H., Dvorkin Y., Qiu T., Wang Y., Kirschen D.. Library of the renewable energy analysis lab (REAL), University of Washington, Seattle, USA. https://labs.ece.uw.edu/real/library.html; 2014.
[64] Papaefthymiou G, Pinson P. Modeling of spatial dependence in wind power forecast uncertainty. In: Int. Conf. on Prob. Methods App. to Pow. Syst.. IEEE; 2008. p. 1–9.

[65] Papavasiliou A, He Y, Svoboda A. Self-commitment of combined cycle units under electricity price uncertainty. IEEE Trans on Pow Syst 2014;30:1690–701.
[66] Pineda S, Morales JM. Capacity expansion of stochastic power generation under two-stage electricity markets. Computers & Oper Res 2016;70:101–14.
[67] Poplavskaya K, De Vries L. Distributed energy resources and the organized balancing market: a symbiosis yet? case of three european balancing markets. Energy Policy 2019;126:264–76.
[68] Pritchard G, Zakeri G, Philpott A. A single-settlement, energy-only electric power market for unpredictable and intermittent participants. Oper Res 2010;58:1210–19.
[69] Ruiz PA, Contreras J. An effective transmission network expansion cost allocation based on game th. IEEE Trans on Pow Syst 2007;22:136–44.
[70] Schmeidler D. The nucleolus of a characteristic function game. SIAM J on App Math 1969;17:1163–70.
[71] Shapley LS. On balanced sets and cores. Naval Res Logistics Quarterly 1967;14:453–60.
[72] Shapley LS, Shubik M. Quasi-cores in a monetary economy with nonconvex preferences. Econ 1966:805–27.
[73] Shapley LS, Shubik M. On market games. J of Econ Theory 1969;1:9–25.
[74] Soares I, Alves MJ, Antunes CH. Designing time-of-use tariffs in electricity retail markets using a bi-level model–estimating bounds when the lower level problem cannot be exactly solved. Omega (Westport) 2020;93. 102–027.
[75] Solis IAA. Analysis of renewable energy integration in transmission-constrained electricity markets using parallel computing; 2018. Ph.D. thesis
[76] Spiecker S, Weber C. The future of the European electricity system and the impact of fluctuating renewable energy–a scenario analysis. En Pol 2014;65:185–97.
[77] Swider DJ, Weber C. Bidding under price uncertainty in multi-unit pay-as-bid procurement auctions for power systems reserve. Eur J of Oper Res 2007;181:1297–308.
[78] Wang T, Deng S. Multi-period energy procurement policies for smart-grid communities with deferrable demand and supplementary uncertain power supplies. Omega (Westport) 2019;89:212–26.
[79] Wong S, Fuller JD. Pricing energy and reserves using stochastic optimization in an alternative electricity market. IEEE Trans on Pow Syst 2007;22: 631–638.
[80] Zakeri G, Pritchard G, Bjorndal M, Bjorndal E. Pricing wind: a revenue adequate, cost recovering uniform price auction for electricity markets with intermittent generation. INFORMS J on Opt 2018;1:35–48.