Electrical Power and Energy Systems 173 (2025) 111441

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

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

Efficient cost allocation in capacity remuneration mechanisms: applying cost causation to resource adequacy

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ARTICLE INFO

Keywords:
Resource adequacy
Capacity mechanisms
Cost allocation
Firm supply
Demand response

ABSTRACT

Capacity Remuneration Mechanisms (or CRMs) have become widespread in liberalised power systems as a regulatory tool to ensure resource adequacy. As these mechanisms have grown in importance, so have the associated costs. However, the methods used to allocate CRM costs remain far too simplistic, failing to provide electricity consumers with adequate economic signals. In this article, we propose allocating CRM costs based on cost causation by calculating each consumer's negative marginal impact on the system's reliability standard. This methodology results in the definition of hourly cost-allocation factors that can ultimately be used to allocate CRM costs to any demand profile. We quantitatively evaluate the methodology through two case studies: a stylised study to illustrate the underlying concepts and a full-scale study inspired by the Spanish power system. These case studies demonstrate that CRM costs should not be allocated exclusively to peak demand; rather, they should be distributed across each hour according to the impact that an additional unit of demand in that hour would have on the system's reliability metric.

1. Introduction and literature review

In recent decades, Capacity Remuneration Mechanisms (CRMs) have become a key component of electricity market design. First introduced in Latin America, CRMs have since spread to the United States and, more recently, the European Union. Discussions on how to reform the European electricity market design over the last decade have highlighted the need for CRMs to ensure resource adequacy as power systems decarbonise [1,2]. Initially considered a transitional tool for addressing specific adequacy issues, following the 2024 Electricity Market Design Reform [3], CRMs are now intended as a permanent feature of the European internal electricity market design..

Capacity mechanisms ensure the security of the electricity supply by providing a long-term investment signal that complements short-term electricity market prices [4–7]. These mechanisms aim to incorporate sufficient firm supply to meet the reliability standard set by the regulator [8], which is commonly expressed in terms of EENS (Expected Energy Non-Served), LOLP (Loss of Load Probability), or LOLE (Loss of Load Expectation). Although CRMs have often been criticised for mainly targeting thermal fossil-driven resources [9], they have recently attracted the participation of non-conventional resources, such as renewable energy sources (RES), battery energy storage (BESS), and demand response (DR) resources. The academic literature has focused on how these technologies, especially wind power [10–13], other renewables [14–17], and BESS [18–22], can enhance the resource adequacy of power systems within the CRM context.

In recent decades, an increasing number of European power systems have implemented CRMs to address concerns about resource adequacy [23]. While consumers in these sectors ideally benefit from enhanced reliability, they also face additional costs on their electricity bills. In the European Union, the surge in the number of power systems relying on CRMs, coupled with the need to manage mounting reliability risks, has resulted in rapid growth in the proportion of total electricity supply costs attributed to these mechanisms, as illustrated in Fig. 1.

It is therefore crucial to allocate these growing CRM costs efficiently to consumers and send economic signals that discourage consumption patterns driving inefficient investment in new firm capacity. This goal could be achieved by applying cost causation. According to this principle, end users should pay rates that reflect the costs imposed on the system by their usage. Cost causation should inform the design of electricity tariffs and is widely applied to various costs in the electricity supply chain [25,26], particularly distribution network costs [27–30]. Some authors have also emphasised the importance of tariffs and charges based on cost causation for the development of demand

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https://doi.org/10.1016/j.ijepes.2025.111441
Received 19 May 2025; Received in revised form 6 November 2025; Accepted 1 December 2025
Available online 9 December 2025

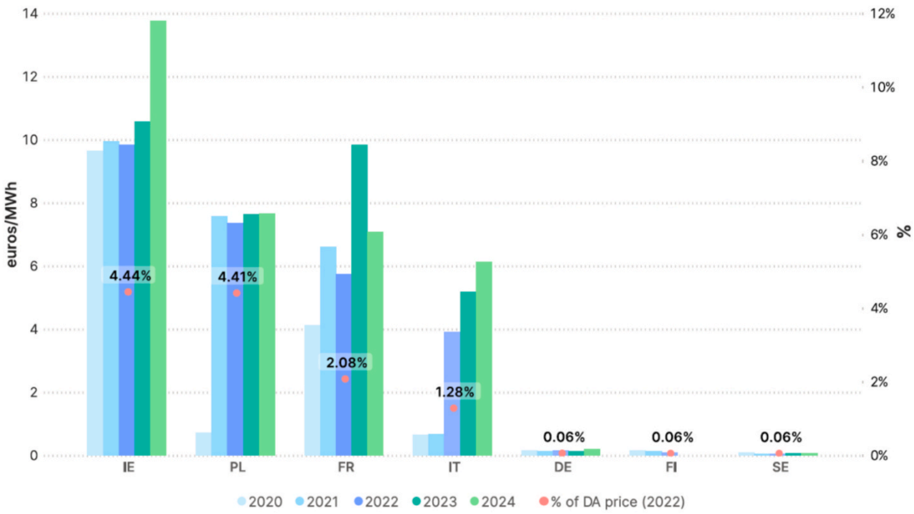

Fig. 1. Costs incurred or projected for the financing of capacity mechanisms per unit of demand and expressed as a percentage of the average annual day-ahead price in a selection of EU Member States [24].

response [31].

However, many electricity systems use simplistic allocation methodologies for CRM costs that do not focus on the true cost drivers of these mechanisms, as discussed below, and result in a socialisation of CRM costs to different extents, which is contrary to the principle of cost causation.

- In Ireland, CRM costs are recovered through volumetric charges applied to consumption between 07:00 and 23:00 each day [32]. These charges signal that consumption during these hours is equally detrimental to the system's reliability, while consumption outside this period has no effect.
- The cost of CRM is recovered through a series of volumetric consumption charges, which vary according to consumer category. Consequently, some consumers face charges that are almost 100 times higher than those faced by others, despite their impact on system reliability potentially being similar [33].
- Italy seeks to recover 70 % of its CRM costs by applying charges to demand during the 500 h of the year when reliability risk is expected to be the highest. The remaining 30 % is recovered through lower charges applied to consumption during the remaining hours of the year [34].
- In Spain, where a CRM is currently being designed [35], the cost of the CRM is expected to be recovered through volumetric charges that vary according to the tariff segment (determined by the connection voltage and contracted power) and the tariff period (peak, flat, or valley), as defined by Spanish network tariff regulations. CRM costs are allocated to each tariff period according to the risk of a firm capacity shortfall, using an index calculated as the ratio of contracted firm capacity to whole-system demand.

Despite the growing significance of CRM costs and the inefficiencies that can stem from simplistic allocation methods, few articles on the subject have been published in academic literature. For instance, some researchers argue that most CRM costs should be allocated to consumption during peak demand periods [36]. Meanwhile, considerable research has been conducted on calculating the contribution of demand response to supply security [18,19,37–41] and on properly integrating demand response resources into CRMs [42,43]. However, calculating firm supply and allocating CRM costs are two sides of the same problem and should be strongly coordinated to avoid inefficiencies and arbitrage opportunities. To the best of the authors' knowledge, this is the first scientific article to put forward a comprehensive proposal for the efficient allocation of CRM costs.

Rodilla et al. (2023) [44] first proposed allocating CRM costs to consumers based on their anticipated negative impact on system reliability. Building on this research and that of Brito-Pereira et al. (2022) [45], this article presents an easy-to-implement methodology for allocating CRM costs based on consumers' marginal negative impact on system adequacy. This methodology enables the calculation of hourly factors reflecting the marginal impact of load variations on the reliability standard. These factors make it possible to identify the hours that are most critical for system reliability. This methodology is then quantitatively evaluated using a convolution-based probabilistic model in two case studies, a stylised example to illustrate the results of the calculation and a full-scale case study inspired by the Spanish power system. The proposed methodology can be applied to real power systems in various ways, some of which are outlined in Rodilla et al. (2023) [44] and summarised in the following section.

The article is structured as follows. Section 2 provides a detailed description of the proposed theoretical cost allocation methodology and demonstrates how it can be used to calculate hourly charges for consumers. Section 3 details the materials and methods used to evaluate the outcomes of this methodology. Section 4 presents case studies used for quantitative assessment of the methodology and discusses the results. Section 5 draws conclusions and makes policy recommendations based on the results of the case studies and the theoretical discussion presented in this article.

2. Efficient CRM cost allocation

Capacity remuneration mechanisms aim to address concerns about system adequacy by providing incentives for resources to help the system meet a certain reliability standard. These incentives encourage market participants to implement both new investments and operational strategies that are consistent with meeting this standard.

As presented in Brito-Pereira et al. (2022) [45], each resource should ideally receive remuneration from the CRM that is proportional to its marginal contribution to meeting the reliability standard. More specifically, the remuneration should be proportional to the following expression0F[1]:

[1] This expression is also proportional to the firm supply that is recognised to each resource in the mechanism.

$$\frac{\partial \mathrm{RM}}{\partial \mathrm{K_i}} \mathrm{K_i} \tag{1}$$

Where:

- The sub-index i refers to the generation asset under consideration.
- K_i is the installed capacity of resource i (expressed in MW)
- RM is the reliability metric used by the regulator (or system operator) to set the reliability standard.

The marginal contribution of each resource depends on the characteristics of the system (demand, load profile, existing generation, storage technologies, etc.), the characteristics of the resource (availability, production profile, etc.), and the chosen reliability standard. If, for the same system, a different metric (e.g., LOLP instead of EENS) is used to define the reliability standard, the marginal contribution will most likely change and therefore the remuneration of different resources would also change.

Just as resources providing adequacy services should be remunerated in proportion to their positive marginal contribution to the reliability standard, consumers should ideally be allocated CRM costs in proportion to their negative marginal contribution, in line with the cost causation principle. Annex I presents an alternative, yet equivalent, formulation to the one described by Brito-Pereira et al. (2022) [45], which is more suitable for methodologies to allocate CRM costs to demand. This formulation replaces the installed capacity variable (the key variable on the generation side) with hourly consumption (the key variable on the demand side). With this new formulation, we derive the expression providing the cost to be allocated to any consumer i:

$$\sum_h \frac{\partial \mathrm{RM}}{\partial \mathrm{D^h}} \mathrm{D_i^h} \tag{2}$$

Where:

- The super-index h refers to hourly values.
- ∂RM is the variation in the reliability metric registered after a marginal increase in demand in a certain hour $\partial \mathrm{D^h}$.
- $\mathrm{D_i^h}$ is the hourly, h, demand of consumer i (expressed in MWh)

We refer to the term $\frac{\partial \mathrm{RM}}{\partial \mathrm{D^h}}$ as the "hourly marginal reliability factor" for hour h. This term reflects the impact of a marginal increase in demand in that hour on the system reliability metric. For example, the marginal reliability factor for an hour when the system is under stress may be double that for a low-demand hour. Therefore, consumption in the first hour should account for twice the proportion of CRM costs as consumption in the second hour.

If each consumer's load profile is multiplied by the hourly marginal reliability factors over a certain time horizon and then all the hourly values obtained are summed, the result is what we refer to in this article as the "cost allocation weight" for consumer i (the term in equation 2). These weights indicate how much a consumer should pay compared to others and can be expressed as percentages, or "cost allocation shares", which can be multiplied directly by the total CRM cost.[2] This enables cost causation to be applied to the allocation of CRM costs among consumers, encouraging more efficient demand behaviour and incentivising the development of demand response [31]. In the context of the sustained electrification of electricity demand, which should be a pillar of the energy transition, activating demand during stress events is crucial to ensuring the security of the electricity supply.

As outlined by Rodilla et al. (2023) [44], the proposed methodology can be applied to real capacity mechanisms in various ways. The hourly marginal reliability factors calculated according to this methodology can be multiplied by the load profile of different consumers or groups of consumers. These factors can be calculated either ex ante using historical data or projections of future system behaviour, or ex post using actual system operation data. Each approach has its own advantages and disadvantages, particularly with regard to the strength of the economic signal conveyed to consumers by the resulting charges, as analysed in [44]. A thorough discussion of the trade-offs involved in selecting data inputs is beyond the scope of this article, which focuses on the underlying methodology.

3. Materials and methods

The theoretical approach presented in section 2 is applied to a convolution-based probabilistic production cost (PPC) model, which allows us to demonstrate the advantages of the proposed methodology in a rather straightforward and illustrative way. Probabilistic reliability assessment is required in order to calculate the reliability metric and to assess the impact of a marginal increase in demand in each hour.

PPC models are well-known classic tools that have traditionally been used to assess power system reliability [46]. These models attempt to calculate the loss of load and the non-served energy in the system through probabilistic functions of the electricity demand and the energy output from generators. To account for all possible combinations of power plant outages, these models use a convolutional process [47,48]. PPC models have several strengths, including low modelling complexity and computational time, while they can accurately represent power plant outages and the stochastic nature of load. However, these models lack a time-sequential representation of system dispatch and do not incorporate some technical aspects of generators, such as ramping constraints and minimum down-times. However, for the purposes of our analysis, convolution-based PPC models are a useful tool to illustrate and demonstrate the methodology proposed in this article and its application to CRM cost allocation. It should be noted, however, that the theoretical approach described above can be applied to more sophisticated simulation models, as those used in resource adequacy assessments.

In PPC models, the probabilistic distribution of electricity demand is usually obtained by analysing historical demand patterns over a given time period. This can be done in two steps: first, by transforming the historical hourly electricity demand into a load duration curve, where the hourly demand is ordered from higher to lower values (Fig. 2), and second, with the subsequent transformation of the load duration curve into a complementary distribution function (Fig. 3). The complementary distribution function will reflect the probability of the demand exceeding a certain level for any generic time interval (in this case, hours).

In order to consider all possible combinations of availability and unavailability of generators, a convolution process is applied to the

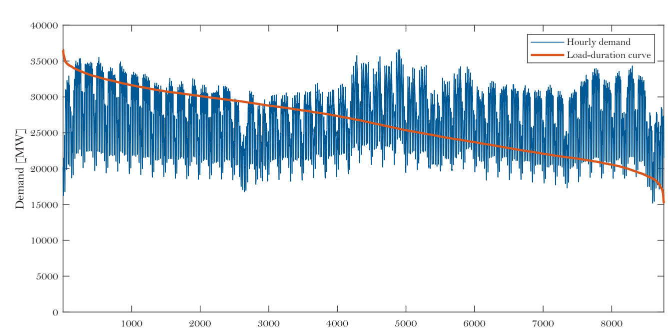

Fig. 2. Spanish 2019 hourly electricity demand and its transformation into a load duration curve.

[2] As with the generation side, it should be noted that if a different metric is used to calculate hourly marginal reliability factors, the cost allocation shares will most likely change, as will the allocation of CRM costs among consumers.

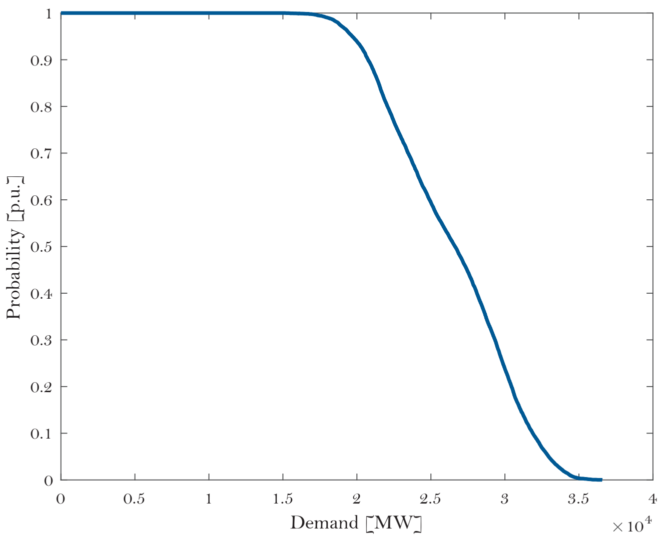

Fig. 3. Complementary distribution function of electricity demand in the system.

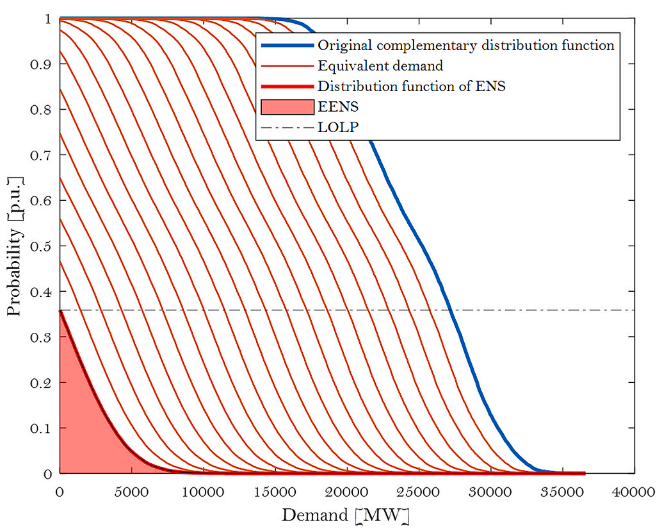

Fig. 4. Application of the convolution process to the complementary distribution function of electricity demand.

probability distributions of the generators. The convolution process consists of calculating the equivalent demand after probabilistic dispatching of n generators.[3] As generation assets are progressively included in the assessment according to an economic merit order, the equivalent demand reveals the probability distribution function of the non-served energy in the system, which would progressively decrease as more generators are added to the convolution, as shown in Fig. 4. The EENS can be obtained as the area defined by the distribution function of the non-served energy (i.e., the equivalent demand after having included all N generators), while the LOLP can be obtained as the intercept of the same function on the y-axis.

PPC models can be used to calculate the hourly marginal reliability factors as defined in section 2, which reflect the impact of a marginal increase in demand in a given hour on the reliability metric. The original complementary distribution function of electricity demand is modified to account for a marginal increment in hour h. The convolution process is repeated and a new value of the reliability metric is calculated. The change in the reliability metric (*RM*) after adding a marginal increment of demand in hour h (D^h) is the hourly marginal reliability factor for hour h ($\frac{\partial RM}{\partial D^h}$), as expressed in equation 2. The process must be repeated for all the hours in the time horizon, in this case for 8760 h, resulting in 8760 hourly marginal reliability factors.

4. Case studies: results and discussions

The methodology described in section 3 is applied here to two case studies. The first is a stylised case study used to better illustrate the methodology and its outcomes. The second is a full-scale case study, inspired by the Spanish power system, which is used to discuss how CRM costs should be allocated to consumers. Both case studies are based on an EENS reliability metric.

5. Stylised case study

In the stylised case study, the methodology is applied to a 24-hour load, which is divided between six consumers with different demand profiles, as shown in Fig. 5. The generation mix serving this demand consists of ten 1-MW CCGTs, each with an Equivalent Forced Outage Rate (EFOR) of 0.1.

The first step in the methodology is to calculate the hourly marginal reliability factors using the procedure presented in section 2. The results are shown in Fig. 6. As we use EENS as the reliability metric, both the variation in the reliability metric and the marginal increase in the demand are expressed in MWh and the factors, which are the ratios of these two terms, are then expressed on a per-unit basis.

The highest marginal reliability factors are recorded during periods of higher demand, such as between 9:00 and 10:00 and 19:00 and 20:00. It should be noted that the factors are not linearly proportional to electricity demand. For example, although the evening peak is only 1 MW higher than the morning peak (12.5 % higher), the marginal reliability factor for the evening peak is almost four times higher than that corresponding to the morning peak.

It should also be noted that the marginal reliability factors for the first eight hours and the last three hours of the day are very low (1.18 x 10^{-5} and 1.18 x 10^{-8}, respectively), but they are not zero. These values reflect that, although most of the CRM costs should be allocated to the hours with the highest risk of scarcity (in this case, the peak-demand hours), no hour has a zero marginal EENS or a zero marginal reliability factor, and some of the CRM costs should be allocated to the off-

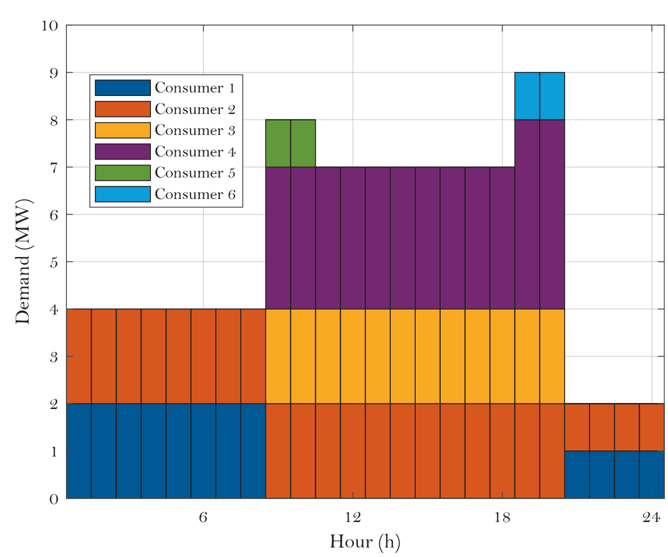

Fig. 5. Consumer demand profiles in the stylised case study.

[3] In most PPC models, generators are either available at full capacity or completely unavailable. Each generator (i) has a probability p_i to be fully available and a probability q_i (q_i=1-p_i) of being unavailable.

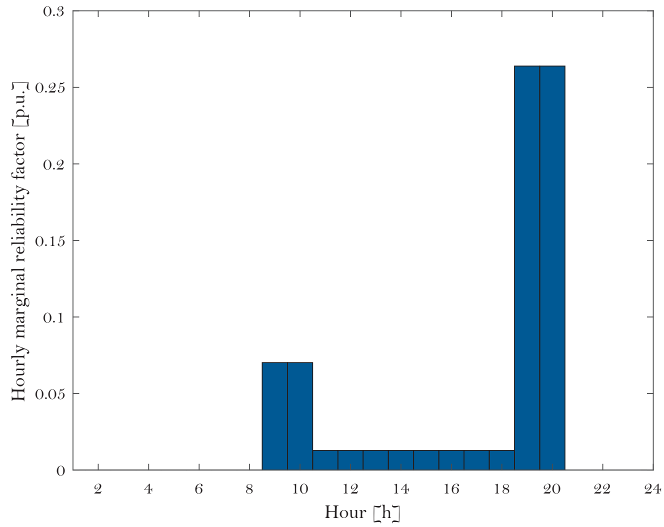

Fig. 6. Hourly marginal reliability factors for the 24-hour time horizon of the stylised case study.

peak hours.

To determine the share of the CRM costs to be borne by each of the six consumers, the hourly marginal reliability factors should be multiplied by the consumption profile of each consumer. For the sake of clarity, both variables are shown together in Fig. 7.

The result of these multiplications is the cost allocation weight for each consumer profile, as presented in Table 1. These cost allocation weights can also be expressed as percentages, representing the proportion of CRM costs that should ideally be allocated to that consumer. In addition, if the cost allocation weights are divided by the total demand of each consumer, they can also be expressed on a unit basis, allowing for a more straightforward comparison between them.

The results show that consumer 6 has the highest unitary cost allocation weight because it only uses electricity during the hours with the highest risk of shortage, when the marginal reliability factor is the highest. On the contrary, consumer 1, who only consumes during off-peak hours, has the lowest unitary cost allocation weight. In terms of cost allocation share, the largest share of CRM costs should be borne by consumer 4, who has a high demand and withdraws electricity during both the morning and evening peaks. Consumer 1, who only has off-peak demand, would have to pay a small but still positive percentage of the total CRM costs.

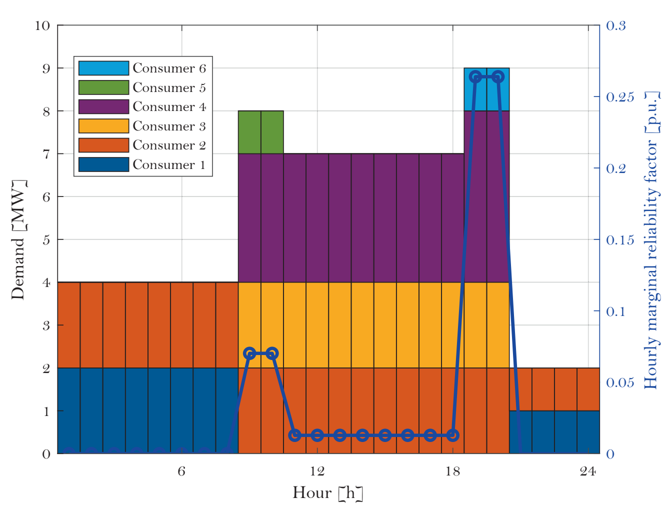

Fig. 7. Hourly marginal reliability factors and consumption per consumer.

Table 1
Cost allocation weights and shares for the stylised case study.

Consumer	Cost allocation weights	Cost allocation share	Unitary cost allocation weights
1	1.46 x10^{-4}	0.002 %	1.75 x10^{-4}
2	1.5412	23.387 %	0.8407
3	1.5411	23.385 %	1.5411
4	2.8394	43.086 %	1.7933
5	0.1404	2.130 %	1.6846
6	0.5278	8.009 %	6.3336

Table 2
Electricity mix used for the full-scale case study.

Technology	Number of units	Installed capacity per unit (MW)	EFOR (p.u.)
Nuclear	15	500	0.015
Fuel Oil	10	500	0.100
CCGT	50	500	0.050
OCGT	5	250	0.200

6. Full-scale case study

The full-scale case study is based on the hourly demand of the Spanish power system in 2019, as shown above in Fig. 2, together with the corresponding load duration curve. For the sake of simplicity and due to the intrinsic limitations of PPC models (which cannot account for the time sequential intermittency of renewable energy sources or the energy constraints of electricity storage), the generation mix modelled in the full-scale case study only includes conventional thermal generation units. The installed capacity of these generators has been calibrated to achieve a normalised EENS in the system equal to 0.002 %1F.[4] The total installed capacity in the system to achieve this reliability standard (assessed with the PPC model) is 38 750 MW, with the technology mix2F[5] described in Table 2.

Unlike the stylised case study, which has a 24-hour time horizon, the full-scale case study evaluates an entire year of hourly data. Using the same methodology described for the stylised case study, it is possible to calculate the marginal reliability factors for each hour of the year. Fig. 8 presents this information as a heatmap, showing the 52 weeks of the year on the vertical axis and the 168 h in each week on the horizontal axis. As intermittent renewable resources are not included in the model, the hours with the highest marginal reliability factors (representing the highest risk of scarcity) appear in the middle hours of summer days, when demand is higher. On the other hand, the weekends (corresponding to the last two vertical sections of the heatmap) and the early hours of the weekdays have the lowest marginal reliability factors and, therefore, the lowest adequacy risk for the system.

Following the same reasoning as in the stylised case study, the hourly marginal reliability factors can be used to determine the cost allocation share of any load profile. For this case study, three different demand profiles are evaluated, reflecting very different consumption patterns, as shown in Fig. 9. Consumer 1 only withdraws electricity in the early hours of the day, when the reliability risk is lower, consumer 2 only consumes during the peak hours of the day, and consumer 3 has a more balanced load, which may resemble that of a residential consumer. Each of these consumer profiles is repeated over the 365 days of the year and, for ease of comparison, has an identical annual demand of 8760 MWh.

[4] This is the reliability standard used in AEMO [49], which is expressed as normalised EENS and can be easily transposed from one system to another. The normalised EENS is obtained by dividing the EENS by the total demand in the system in the same time horizon.

[5] Many generation mixes could meet the same target, but this would not significantly change the results of the simulation or the key messages of this paper.

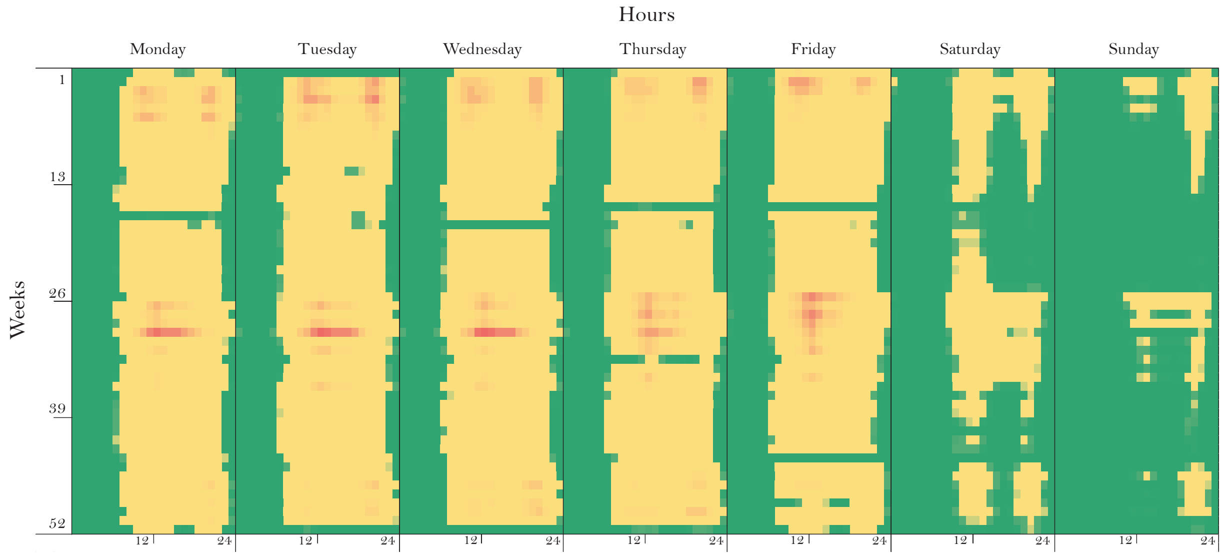

Fig. 8. Heatmap of the hourly marginal reliability factors for the full-scale case study.

Again, each consumer's cost allocation weight and share can be obtained by multiplying its hourly consumption by the hourly marginal reliability factors. The results are presented in Table 3. The three consumption profiles considered in the full-scale case study represent only a small fraction of the demand in the system, and therefore their cost allocation shares are very small in percentage terms. However, these shares are used here to show the comparative difference between the profiles.

These results show how consumer 1, who only withdraws electricity at night, would have to pay a very small but still positive share of the CRM cost. Consumer 2, who only consumes during peak hours, has a cost allocation share that is more than three times higher than that calculated for consumer 3, even though they have the same total demand during the year.

It should be emphasised that the cost allocation shares also depend on the reliability standard. The latter has an impact on the expected scarcity conditions in the system and the time intervals in which they are more likely to occur. As a sensitivity analysis, the full-scale case study was run for a reliability standard of normalised EENS equal to 0.05 % (i.e., with a resource mix with fewer generation units and a higher risk of scarcity than in the previous run). The new cost allocation shares of the three consumers are shown in Table 4.

Table 3
Cost allocation shares for the full-scale case study with a 0.002% normalised EENS.

Consumer	Cost allocation share
1	$0.011 \cdot 10^{-3}$ %
2	$10.051 \cdot 10^{-3}$ %
3	$3.066 \cdot 10^{-3}$ %

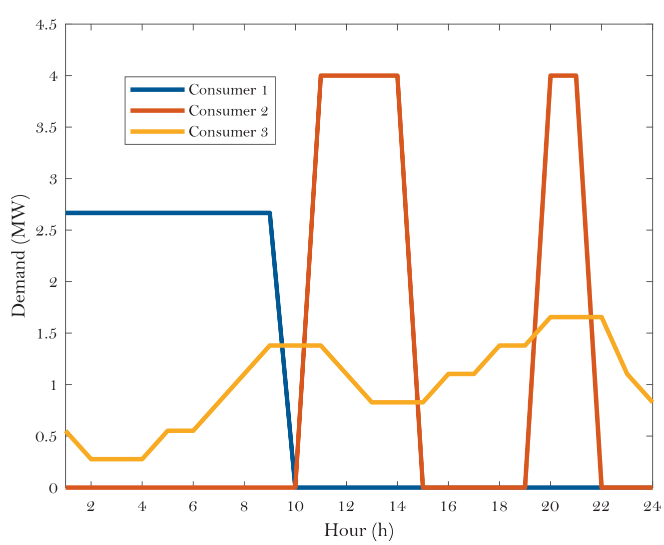

Fig. 9. Consumer profiles to determine cost allocation in the full-scale case study.

In this case, consumer 1 has a higher cost allocation weight, more than six times higher than with a 0.002 % EENS, and would have to pay a larger share of the CRM costs. In fact, with a normalised EENS of 0.05 %, the system registers many more scarcity conditions and they are more likely to occur during the off-peak hours, when consumer 1 withdraws electricity. For the same reason, consumer 2 has a lower cost allocation share (10 % lower with a 0.05 % normalised EENS than with a 0.002 % normalised EENS) and would have to pay a lower share of the CRM costs.

These results reflect the application of the cost-causation principle to CRM cost allocation. The methodologies used for CRM cost allocation in most European power systems are based on strategies that prioritise simplicity, but these strategies may convey inefficient signals. As mentioned in the introduction, Ireland recovers CRM costs through volumetric charges applied to consumption between 07:00 and 23:00 each day [25]. In our case study, this cost allocation strategy would result in the cost allocation shares presented in Table 5.

Under the Irish cost allocation strategy, consumer 2 would pay half of what they should pay if cost causation were applied, while consumers 1 and 3 would pay a higher share of CRM costs.

Table 4
Cost allocation shares for the full-scale case study with a 0.05% normalised EENS.

Consumer	Cost allocation share
1	$0.072 \cdot 10^{-3}$ %
2	$9.114 \cdot 10^{-3}$ %
3	$3.473 \cdot 10^{-3}$ %

Table 5
Cost allocation shares for the full-scale case study based on the Irish CRM cost allocation strategy.

Consumer	Cost allocation share
1	$1.668 \cdot 10^{-3}$ %
2	$5.003 \cdot 10^{-3}$ %
3	$4.313 \cdot 10^{-3}$ %

7. Conclusions and policy implications

In recent decades, CRMs have become one of the main pillars of electricity market design. In the European Union, capacity mechanisms are now widespread, and the associated costs are steadily rising. It is therefore becoming increasingly important to allocate these costs efficiently and refine current methodologies, which tend to be simplistic and focus solely on cost recovery. The efficient allocation of CRM costs should send the right economic signals to consumers, encouraging them to reduce their electricity usage during periods when the system is at higher risk of scarcity. In the long term, this would also reduce demand for firm supply covered by the capacity mechanism, thereby reducing the overall cost of electricity supply.

This article proposes an efficient cost allocation methodology for CRMs that is based on cost causation. This is achieved by calculating hourly marginal reliability factors that reflect the impact on the reliability metric of a marginal increase in load in that hour. These factors can then be used to calculate cost allocation weights for each consumption profile, reflecting the proportion of total CRM costs to be allocated to each consumer. The results of the quantitative analysis presented in this article demonstrate that CRM costs should not be allocated exclusively to peak demand, as is common practice in many electricity systems, but rather to each time interval based on the impact that a marginal increase in demand during that interval has on the system's reliability metric. While peak demand hours (or peak residual demand hours in systems with high renewable energy penetration) may have a greater impact on CRM cost allocation, off-peak hours also have a non-zero probability of scarcity conditions.

Although it would require greater computational effort, the methodology presented in this article could be applied to more complex modelling techniques, such as those commonly used for resource adequacy assessments (e.g., Unit Commitment models), in order to incorporate all technologies and their associated constraints, and to achieve more accurate results. Future work should investigate how to calculate hourly marginal reliability factors and cost allocation weights using UC models and consider the resulting computational burden. This would allow to include intermittent renewable and storage resources in these models. Furture work should also assess the impact of using reliability metrics other than EENS, since the marginal contribution of each demand profile depends on the chosen reliability standard, as mentioned in the introduction. Another aspect that should be further assessed is whether the proposed methodology should be applied ex ante, based on historical data or projections, or ex post, according to actual system operation data. Future work could quantitatively assess the impact of each approach on the economic signals conveyed by the resulting charges.

The assessment presented in this article is closely related to the participation of demand resources in capacity mechanisms. The proposed methodology enables the cost allocation weight to be calculated for each consumption profile, which can also be considered as the firm supply demand that the profile imposes on the system. Clearly, this value sets a baseline for any consumer participation in the CRM, as it reflects the maximum negative contribution that the consumer can offset by activating and reducing her demand during stress events. Applying the same methodology to the negative demand profile that a consumer is willing to offer as a demand response would also make it possible to calculate the firm supply that the demand response resource can offer to the system. As mentioned by Rodilla et al. (2023), using the same methodology for cost allocation and calculating firm supply eliminates arbitrage opportunities, allowing for more efficient demand response participation in CRMs. This additional aspect of the methodology proposed in this article should be explored further in future work.

CRediT authorship contribution statement

Paulo Brito-Pereira: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis. **Pablo Rodilla:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization. **Paolo Mastropietro:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization.

Declaration of competing interest

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

Acknowledgments

The authors would like to thank Carlos Batlle from the Universidad Pontificia Comillas for his assistance in defining the theoretical framework of this article. Pablo Rodilla and Paolo Mastropietro have been supported by the DEFINER research project, funded by the Spanish Ministry of Science and Innovation and the Spanish State Research Agency (grant number CPP2021–008786).

Appendix

Annex I

This section demonstrates the link between the reliability metric, the computation of the firm supply and how this firm supply should be remunerated. Additionally, this section demonstrates how to determine how much firm supply each consumer is demanding and therefore how much it should pay for it.

This section is based on Annex I of Brito-Pereira et al. (2022) [45], in which a stylised version of the ideal central planner problem is solved and compared to the individual agent problem. Comparing both optimality conditions allows us to draw several important conclusions.

The main difference between Brito-Pereira et al. (2022) [45] and the developments presented in this section is that the reliability target set in the centralised problem is presented as a function of generation and demand, not only as a function of the installed capacity (since the focus is now expanded to the demand side, and, therefore, the hourly consumption becomes a variable). Finally, we present the problem from the perspective of an individual consumer.

Centralised problem

This subsection uses a stylised version of the regulator's model presented by Pérez-Arriaga and Meseguer (1997) [50]. In this problem, the objective is to maximise the net social benefit, *NSB*, related to the supply and consumption of electricity. This *NSB* is represented by the following expression:

$$\underset{D\ Q\ K\ NSE}{\mathrm{Max}}\ \mathrm{NSB} = \mathrm{U(D)} - \mathrm{C(Q)} - \mathrm{I(K)} - \mathrm{NSEC(NSE)} \tag{1}$$

Where:

- *D* represents the full set of elements $\{D_{j,h}\}$, which in turn correspond to the hourly, h = 1,2,3,4,…H, demand of each consumer, j = 1,2,3,4,…m.
- *U(D)* is the demand utility function, which depends on the hourly power consumed by the demand. This demand utility function is assumed to be strictly increasing and concave.
- *Q*, represents the full set of elements $\{Q_{j,h}\}$, which in turn correspond to the hourly production of each generating unit, i = 1,2,3,4,…n.
- *C(Q)* is the generation cost function, which depends on the hourly generation of each of the generation units. In this case, the function is assumed to be strictly increasing and convex.
- *K* represents the full set of elements $\{K_j\}$, which in turn correspond to the installed capacity of each generating plant, i = 1,2,3,4,…n.
- *I(K)* is the investment cost function which depends on the installed capacity of each generation unit. In this case, the function is assumed to be strictly increasing and convex.
- *NSE* represents the full set of elements $\{NSE_h\}$, which in turn correspond to the non-served demand of each hour, h = 1,2,3,4,…H.
- *NSEC(NSE)* represents the hourly cost associated with the hourly non-served demand due to limited generation capacity. In this case, the function is assumed to be strictly increasing and convex.

This stylised representation only considers three constraints:

$$\sum\nolimits_{j=1}^{m} \mathrm{D_{j,h}} \ \leq \ \sum\nolimits_{i=1}^{n} \mathrm{Q_{i,h}} + \mathrm{NSE_h}\ \forall \mathrm{h} \in \mathrm{H}\ (\pi_\mathrm{h}) \tag{2}$$

$$\mathrm{Q_{i,h}} \ \leq \ \mathrm{K_i}\ \forall \mathrm{h} \in \mathrm{H},\ [\mathrm{REVEAA}]\mathrm{i} \in \mathrm{n}\ (\alpha_{\mathrm{i,h}}) \tag{3}$$

$$\mathrm{RM(K, D)}\ [\mathrm{GRTEQT}]\ \mathrm{RT}(\beta) \tag{4}$$

The first constraint represents the balance between the hourly demand and generation, with the inclusion of non-served energy allowing for some part of the demand not to be satisfied if this were economically efficient.

The second constraint represents the upper limit of the power produced by each generation unit *i* in hour *h*, which corresponds to the installed capacity of that unit, K_i.

On the other hand, the third constraint forces the reliability metric, *RM*, to fulfil a certain reliability target, *RT*, which is set as a parameter. The *RM* is assumed to be strictly decreasing and convex. In Brito-Pereira et al. (2022) [38], this reliability metric was assumed to be dependent only on the electricity mix, $RM(K_1, K_2, K_3,\ldots K_n)$. In this case, we expand on this formulation and make it dependent also on the system demand, which is coherent because the reliability of the system will depend on its installed capacity in relation to the electricity demand in the system.

For simplicity, we have therefore discarded other operation constraints such as ramps, minimum power outputs, etc.

In order to obtain the first-order necessary conditions, we formulate the Lagrangian function, L, and compute its first partial derivatives with respect to the decision variables.

$$\mathrm{L}(\mathrm{Q, D, K}, \pi_\mathrm{h}, \alpha_{\mathrm{i,h}}, \hat{\mathrm{I}}^2) \ = \ \mathrm{U(D)} - \mathrm{C(Q)} - \mathrm{I(K)} - \mathrm{NSEC(NSE)} \ + \sum_{\mathrm{h}=1}^{\mathrm{H}} \left[\left(\sum\nolimits_{j=1}^{m} \mathrm{D_{j,h}} - \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Q_{i,h}} - \mathrm{NSE_h}\right)\pi_\mathrm{h} + \sum_{1}^{\mathrm{n}} \left(\left(\mathrm{Q_{i,h}} - \mathrm{K_i}\right) \bullet \alpha_{\mathrm{i,h}} \right) \right] \ + \ (\mathrm{RM(K, D)} - \mathrm{RT}) \bullet \beta \tag{5}$$

If we compute the first partial derivative of this expression with respect to the decision variable K_i, which is the installed capacity of generator *i*, we obtain the following expression:

$$\frac{\partial \mathrm{L}}{\partial \mathrm{K_i}} = -\sum\nolimits_{\mathrm{h}=1}^{\mathrm{H}} \alpha_{\mathrm{i,h}} - \frac{\partial \mathrm{I(K)}}{\partial \mathrm{K_i}} + \frac{\partial \mathrm{RM(K, D)}}{\partial \mathrm{K_i}}\beta \ = \ 0 \tag{6}$$

If we do the same with respect to the demand of consumer *j*, $D_{j,h}$, we obtain the following expression:

$$\frac{\partial \mathrm{L}}{\partial \mathrm{D_{j,h}}} = \pi_\mathrm{h} + \frac{\partial \mathrm{U(D)}}{\partial \mathrm{D_{j,h}}} - \frac{\partial \mathrm{RM(K, D)}}{\partial \mathrm{D_{j,h}}}\beta = 0 \tag{7}$$

The difference in signs of the partial derivative of the reliability metric is because generation and demand have opposing effects on the reliability metric. An increase in generation capacity would improve the reliability metric, but an increase in demand would worsen the reliability metric.

Decentralised problem

Generator problem

This subsection uses a stylised version of the generators' viewpoint of the competitive market model presented by Pérez-Arriaga and Meseguer

(1997) [43]. In contrast with the centralised problem, the objective of each generation unit, i, is to maximise its own profit, P_i, which is represented by the following expression, where it is assumed that there is both a spot market and a capacity market:

$$\max_{Q_{i,h}\ K_i} P_i = \sum_{h=1}^{H}\left[SMP_{Q,i,h} \bullet Q_{i,h}\right] - C_i(Q_i) + CMP_{K,i} \bullet K_i - I_i(K_i) \tag{8}$$

Where:

- $SMP_{Q,i,h}$ is the hourly spot market price perceived by generation unit i in hour h which, when multiplied by the hourly generation, $Q_{i,h}$, results in the spot market revenues.
- $CMP_{K,i}$ is the capacity market price profile perceived by generation unit i, which, when multiplied by K_i results in the capacity market revenues.
- Q_i represents the full set of hourly generation values of generation unit i.
- $C_i(Q_i)$ and $I_i(K_i)$ are the generation cost function and the investment cost function of generation unit i, respectively, with the same characteristics as the centralised problem.

The only constraint present in this problem is the following:

$$Q_{i,h} \leq K_i \ \forall h \in H \ (\alpha_{i,h}) \tag{9}$$

This constraint is equivalent to the second constraint in the centralised problem. The first and third constraints found in the centralised problem are only present through the regulator's perspective and are therefore only translated through the spot and capacity market prices, respectively, in the objective function in this decentralised problem.

In order to obtain the first-order necessary conditions, we formulate now the Lagrangian function of this second problem, L, and compute its first partial derivatives with respect to the decision variables.

$$L(Q_i, K_i, \alpha_{i,h}) = \sum_{h=1}^{H}\left[SMP_{Q,i,h} \bullet Q_{i,h} + \left(Q_{i,h} - K_i\right) \bullet \alpha_{i,h}\right] - C_i(Q_i) + CMP_{K,i} \bullet K_i - I_i(K_i) \tag{10}$$

When computing the first partial derivative of this expression with respect to the decision variable K_i we obtain the following optimality condition:

$$\frac{\partial L}{\partial K_i} = CMP_{Ki} - \frac{\partial I(K)}{\partial K_i} - \sum_{h=1}^{H} \alpha_{i,h} = 0 \tag{11}$$

Equation 11 is very similar to equation 6, without the global constraint described by equation 4, which is only present in the centralised problem, but with the additional term $CMP_{K,i}$.

Unification of the centralised problem and the generator problem

Comparing equation 11 to equation 6, we obtain the following expression:

$$CMP_{K,i} = \frac{\partial RM(K,D)}{\partial K_i} \bullet \beta \tag{12}$$

This allows us to draw the conclusion that firm supply depends on the marginal contribution to the reliability metric RM, which is the same conclusion presented in Brito-Pereira et al. (2022) [38].

Consumer problem

The consumer problem is very similar to that of the generator, although it does not consider any investment and generation costs. The objective of each consumer, j, is to maximise their personal net benefit, PNB_j, considering their utility function, and both the spot market and capacity market prices:

$$\max_{D_{j,h}} PNB_j = U_j(D_j) - \sum_{h=1}^{H}\left[SMP_{D,j,h} \bullet D_{j,h} + CMP_{D,j,h} \bullet D_{j,h}\right] \tag{13}$$

Where:

- D_j represents the full set of hourly generation values of consumer j.
- $U_j(D_j)$ represents the utility that consumer j obtains by the use of electricity.
- $SMP_{D,j,h}$ is the hourly spot market price perceived by demand j, which, when multiplied by the hourly demand, $D_{j,h}$, results in the spot market disbursements.
- $CMP_{D,j,h}$ is the capacity market price perceived by consumer j, which results in the capacity market disbursements when multiplied by $D_{j,h}$. In CRMs, these disbursements would be allocated as a lump sum either ex-ante, based on estimations of consumer demand, or ex-post, based on actual consumption.

In this case, we do not consider any constraints.

In order to obtain the first-order necessary conditions, we formulate now the Lagrangian function of this second problem, L, and compute its first partial derivatives with respect to the decision variables.

$$L(D_{j,h}) = U_j(D_j) - \sum_{h=1}^{H}\left[SMP_{D,j,h} \bullet D_{j,h} + CMP_{D,j,h} \bullet D_{j,h}\right] \tag{14}$$

When computing the first partial derivative of this expression with respect to the decision variable $D_{j,h}$, we obtain the following optimality condition:

$$\frac{\partial L}{\partial D_{j,h}} = \frac{\partial U_j(D_j)}{\partial D_{j,h}} - CMP_{D,j,h} - SMP_{D,j,h} = 0 \tag{15}$$

Unification of the centralised problem and the *consumer* ***problem***

Comparing equation 15 to equation 7, we obtain equation 16, given that the variation in the utility of consumer *j* due to a marginal variation in its consumption is equivalent to the variation in the utility of demand as a whole (only the utility of consumer *j* will be affected):

$$CMP_{D,j,h} + SMP_{D,j,h} = \frac{\partial RM(K,D)}{\partial D_{j,h}} \bullet \beta - \pi_h \tag{16}$$

If we focus on the capacity market disbursements of consumer *i*:

$$CMP_{D,j,h} \bullet D_{j,h} = \frac{\partial RM(K,D)}{\partial D_{j,h}} \bullet D_{j,h} \bullet \beta \tag{17}$$

This allows us to draw several conclusions:

1. The firm supply demanded by consumer *j* depends on its consumption during scarcity conditions.
2. Accordingly, cost allocation to consumer *j* will also depend on its consumption during instances in which a marginal variation of demand would cause a variation in the reliability metric.

Data availability

Data will be made available on request.

References

[1] Meeus, L., Batlle, C., Glachant, J. M., Hancher, L., Pototschnig, A., Ranci, P., Schittekatte, T., 2022. The 5th EU Electricity Market Reform: A Renewable Jackpot for All Europeans Package?. FSR Policy Brief 2022/59.

[2] Pototschnig, A., Glachant, J. M., Meeus, L., Ranci, P., 2022. Recent Energy Price Dynamics and Market Enhancements for the Future Energy Transition. FSR Policy Brief 2022/5.

[3] European Commission, 2024. Regulation (EU) 2024/1747 of the European Parliament and of the Council of 13 June 2024 amending Regulations (EU) 2019/942 and (EU) 2019/943 as regards improving the Union's electricity market design.

[4] Neuhoff K, De Vries L. Insufficient Incentives for Investment in Electricity Generations. Util Policy 2004;12(4):253–67.

[5] Joskow P. Capacity payments in imperfect electricity markets: need and design. Util Policy 2008;16(3):159–70.

[6] Cramton P, Ockenfels A, Stoft S. Capacity Market Fundamentals. Econ Energy Environ Policy 2013;2(2):27–46.

[7] Petitet M, Finon D, Janssen T. Capacity adequacy in power markets facing energy transition: a comparison of scarcity pricing and capacity mechanism. Energy Policy 2017;103:30–46.

[8] Sanchez Jimenez I, Ribó-Pérez D, Cvetkovic M, Kochems J, Schimeczek C, de Vries LJ. Can an energy only market enable resource adequacy in a decarbonized power system? A co-simulation with two agent-based-models. Appl Energy 2024;360:122695.

[9] Bolton R, Clausen T. Ambiguous interventions: capacity remuneration mechanisms and the politics of energy transition in Britain and Germany. Energy Res Soc Sci 2019;56:101218.

[10] D'Annunzio C, Santoso S. noniterative method to approximate the effective load carrying capability of a wind plant. IEEE Trans Energy Convers 2008;23(2):544–50.

[11] Ensslin C, Milligan M, Holttinen H, O'Malley M, Keane A. Current Methods to Calculate Capacity Credit of Wind Power: IEA Collaboration. IEEE Power and Energy Society 2008 General Meeting: Conversion and Delivery of Electrical Energy in the 21st Century. 2008.

[12] Amelin M. Comparison of capacity credit calculation methods for conventional power plants and wind power. IEEE Trans Power Syst 2009;24(2):685–91.

[13] Söder, L., Tómasson, E., Estanqueiro, A., Flynn, D., Hodge, B. M., Kiviluoma, J., Korpås, M., Neau, E., Couto, A., Pudjianto, D., Strbac, G., Burke, D., Gómez, T., Das, K., Cutululis, N. A., Van Hertem, D., Höschle, H., Matevosyan, J., von Roon, S., Carlini, E. M., Caprabianca, M., de Vries, L., 2020. Review of Wind Generation within Adequacy Calculations and Capacity Markets for Different Power Systems. Renewable and Sustainable Energy Reviews, vol. 119, art. 109540.

[14] Bothwell C, Hobbs B. Crediting wind and solar renewables in electricity capacity markets: the effects of alternative definitions upon market efficiency. Energy J 2017;38:173–88.

[15] Schram WL, Aghaie H, Lampropoulos I, van Sark W. Insights on the capacity value of photovoltaics, community batteries and electric vehicles. Sustainable Energy Grids Networks 2021;26:100421.

[16] Brito-Pereira P, Rodilla P, Mastropietro P, Batlle C. Self-fulfilling or self-destroying prophecy? the relevance of de-rating factors in modern capacity mechanisms. Appl Energy 2022;314:118939. https://doi.org/10.1016/j.apenergy.2022.118939.

[17] Kozlova M, Huhta K, Lohrmann A. The interface between support schemes for renewable energy and security of supply: reviewing capacity mechanisms and support schemes for renewable energy in Europe. Energy Policy 2023;181:113707.

[18] Zhou Y, Mancarella P, Mutale J. Modelling and assessment of the contribution of demand response and electrical energy storage to adequacy of supply. Sustainable Energy Grids Networks 2015;3:12–23. https://doi.org/10.1016/j.segan.2015.06.001.

[19] Zhou Y, Mancarella P, Mutale J. Framework for capacity credit assessment of electrical energy storage and demand response. IET Generation, Transmission & Distribution 2016;10(9):2267–76. https://doi.org/10.1049/iet-gtd.2015.0458.

[20] Zachary S, Wilson A, Dent C. The integration of variable generation and storage into electricity capacity markets. Energy J 2022;43:no. 4.

[21] Gonzato S, Bruninx K, Delarue E. The effect of short-term storage operation on resource adequacy. Sustainable Energy Grids Networks 2023;34:101005.

[22] Wang R, Wang S, Geng G, Jiang Q. Multi-time-scale capacity credit assessment of renewable and energy storage considering complex operational time series. Appl Energy 2024;355:122382.

[23] Ragosa G, Watson J, Grubb M. The political economy of electricity system resource adequacy and renewable energy integration: a comparative study of Britain, Italy and California. Energy Res Soc Sci 2024;107.

[24] ACER, Agency for the Cooperation of Energy Regulators, 2023. Security of EU electricity supply. Technical report.

[25] Milligan M, Ela E, Hodge BM, Kirby B, Lew D, Clark C, et al. Integration of variable generation, cost-causation, and integration costs. Electr J 2011;24, iss. 9:51–63.

[26] Badesa L, Matamala C, Strbac G. Who should pay for frequency-containment ancillary services? Making responsible units bear the cost to shape investment in generation and loads. Energy Policy 2025;196:114379.
[27] Sotkiewicz PM, Vignolo JM. Towards a cost Causation-based tariff for distribution networks with DG. IEEE Trans Power Syst 2007;22(3):1051–60.
[28] Morell-Dameto N, Chaves-Ávila JP, Román GS, T., Dueñas-Martínez, P., Schittekatte, T.. Network tariff design with flexible customers: ex-post pricing and a local network capacity market for customer response coordination. Energy Policy 2024;184:113907.
[29] Picciariello A, Reneses J, Frias P, Söder L. Distributed generation and distribution pricing: why do we need new tariff design methodologies? Electr Pow Syst Res 2015;119:370–6.
[30] de Villena MM, Gautier A, Ernst D, Glavic M, Fonteneau R. Modelling and Assessing the Impact of the DSO Remuneration Strategy on its Interaction with Electricity users. Int J Electr Power Energy Syst 2021;126:106585.
[31] Zhang Y, Fan S, Meng Y, He G. Payment and incentive allocation in demand response based on Cost Causation Principle. IEEE Trans Ind Appl 2025;61(6): 8674–87.
[32] SEM, 2020. SEM Tariffs and Charges: Decision Paper SEM–20–057.
[33] BOG, Belgian Official Gazette, 2021. Program Law 2021-12-27/01.
[34] Terna, 2021. Mercato della Capacità: allegato 1 alla Disposizioni tecniche di funzionamento n.2. Regulations approved with Decree of 28 October 2021.
[35] MITERD, Ministerio para la Transición Ecológica y el Reto Demográfico. Proyecto de Orden por la que se crea un mercado de capacidad en el sistema eléctrico peninsular español. Working document 2024.
[36] Wang H, Shen Z, Wang Y, Wang Y, Hu J, Lan Z, et al. Typical Capacity Remuneration Mechanisms and Enlightenment for an Imperfect Competition Electricity Market. 2023 IEEE 6th International electrical and Energy Conference (CIEEC). Hefei, China 2023;2023:3508–13. https://doi.org/10.1109/CIEEC58067.2023.10167395.
[37] Nolan, S., O'Malley, M., Hummon, M., Kiliccote, S., Ma, O., 2014. A methodology for estimating the capacity value of demand response. 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, USA, pp. 1-5, DOI 10.1109/PESGM.2014.6939174.
[38] Nolan S, Neu O, O'Malley M. Capacity Value Estimation of a Load-Shifting Resource using a coupled Building and Power System Model. Appl Energy 2017; 192:71–82.
[39] Zeng B, Wei X, Sun B, Qiu F, Zhang J, Quan X. Assessing capacity credit of demand response in smart distribution grids with behavior-driven modeling framework. Int J Electr Power Energy Syst 2020;118:105745. https://doi.org/10.1016/j.ijepes.2019.105745.
[40] Freire-Barceló T, Martín-Martínez F, Sánchez-Miralles A, Rivier M, Román GS, T., Huclin, S., Chaves Ávila, J.P., Ramos, A.. Storage and demand response contribution to firm capacity: Analysis of the spanish electricity system. Energy Rep 2022;8:10546–60.
[41] Alves IM, Carvalho LM, Peças Lopes JA. Modeling demand flexibility impact on the long-term adequacy of generation systems. Int J Electr Power Energy Syst 2023; 151:109169. https://doi.org/10.1016/j.ijepes.2023.109169.
[42] Lynch MA, Nolan S, Devine MT, O'Malley M. The impacts of demand response participation in capacity markets. Appl Energy 2019;250:444–51. https://doi.org/10.1016/j.apenergy.2019.05.063.
[43] Lambin X. Integration of demand Response in Electricity Market Capacity Mechanisms. Util Policy 2020;64:101033.
[44] Rodilla P, Mastropietro P, Brito-Pereira P. The Challenge of Integrating demand Response in Capacity Remuneration Mechanisms: Providing a Comprehensive Theoretical Framework. IEEE Power Energ Mag 2023;21(4):64–71. https://doi.org/10.1109/MPE.2023.3269551.
[45] Brito-Pereira P, Mastropietro P, Rodilla P, Barroso LA, Batlle C. Adjusting the Aim of Capacity Mechanisms: Future-Proof Reliability Metrics and firm Supply Calculations. Energy Policy 2022;164:112891. https://doi.org/10.1016/j.enpol.2022.112891.
[46] Sutanto D, Outhred HR, Lee Y. Probabilistic power system production cost and reliability calculation by the Z-transform method. IEEE Trans Energy Convers 1989;4(4):559–66. https://doi.org/10.1109/60.41714.
[47] Lu Z, Li H, Qiao Y. Probabilistic Flexibility Evaluation for Power System Planning considering its Association with Renewable Power Curtailment. IEEE Trans Power Syst 2018;33(3):3285–95. https://doi.org/10.1109/TPWRS.2018.2810091.
[48] Ma J, Liu Y, Zhang S, Wu L, Yang Z. Comprehensive probabilistic assessment on capacity adequacy and flexibility of generation resources. International Journal of Electrical Power and Energy Systems 2023;145:108677. https://doi.org/10.1016/j.ijepes.2022.108677.
[49] AEMO, Australian Energy Market Operator, 2019. 2019 Electricity Statement of Opportunities. Report.
[50] Pérez-Arriaga IJ, Meseguer C. Wholesale Marginal prices in Competitive Generation Markets. IEEE Trans Power Syst 1997;12(2). https://doi.org/10.1109/59.589661.