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SELF-FULFILLING OR SELF-DESTROYING PROPHECY? THE RELEVANCE OF DE-RATING FACTORS IN MODERN CAPACITY MECHANISMS

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Abstract

Capacity mechanisms aim at enhancing mid- to long-term reliability by adding an extra income for generation and demand response resources, based on their firm capacity, a parameter commonly defined by the regulator. The firm capacity is often calculated by multiplying the installed capacity by a de-rating factor, to reflect the expected capability of the resources to contribute to system reliability. Computing de-rating factors is quite a challenging and pivotal task, for any error in its determination can seriously affect the performance of the capacity mechanism.

In this paper, using a two-step model that simulates both the capacity auction and the short-term market, we show that the ex-ante definition of firm capacity influences investment decisions, altering the resulting resource mix and, in the end, the very contribution to the system reliability of the resources. Being aware of this potential mismatch caused by the definition of the firm capacity is fundamental for regulators to avoid paying for something that may be unable to contribute to meet the desired reliability target, or which could even deteriorate system adequacy.

The discussion is illustrated with a case example, focusing on the impact of the definition of solar PV de-rating on the outcome of the capacity mechanism and the reliability of the system.

Keywords

Capacity mechanisms; Reliability; Security of supply; De-rating; Firm capacity; Capacity auctions.

1 INTRODUCTION

Capacity mechanisms have become one of the regulatory pillars of the energy transition of the power sector. The need to decarbonize the economy and to achieve ambitious environmental targets has gradually led governments to introduce policies that affect the electricity market, increasing the risk and uncertainty perceived by stakeholders [1][2][3][4]. In this context, capacity mechanisms aim at providing a long-term risk-hedging tool to investors and guarantee the reliability of the system while it transitions to low-carbon technologies [5][6][7][8][9]. Once implemented only in a small number of liberalised power sectors, especially in the American continent, capacity mechanisms have become increasingly prominent on the regulatory agenda in the last two decades and are now predominant also in Europe [10]. The majority of these capacity markets allow some sort of participation from renewable energy sources [11].

A pivotal element in the design of these regulatory instruments is the so-called firm capacity[1]. According to regulatory theory, the latter should represent the expected contribution that a certain resource will provide to the reliability of the system [12]. Firm capacity is calculated by multiplying the installed capacity of the resource by a de-rating

[1] Firm capacity is a concept commonly used in capacity-constrained power systems, e.g., those dominated by thermal generation. In hydro-dominated systems, reliability mechanisms are based on the concept of firm energy. Both concepts can be encompassed by the expression firm supply. In this article, the expression firm capacity is used because the model simulates a capacity-constrained system.

factor or a capacity credit. Once computed, this firm capacity becomes the upper limit of capacity that the resource can trade in the market. The methodologies to compute the firm capacity or de-rating factors of different resources will have to be updated in the context of the energy transition. The methods currently in use in the majority of capacity mechanisms were developed for power systems with resource mixes very different and much simpler, stabler, and more predictable than the ones presently in place or expected to come on stream in the future. More technological alternatives are now being implemented. The presence of renewable technologies varies the type and magnitude of scarcity affecting power systems and raises the correlation between resource availability and peak load timing. All these factors will have to be internalised in the firm supply calculation.

The goal of this article is not to delve into the methodology to calculate firm capacities or de-rating factors; theoretical analyses on this topic can be found in [12][13][14][15][16][17][18][19][20]. The objective of this paper is to stress and empirically demonstrate the influence that the definition of de-rating factors in the context of a capacity mechanism can have on the electricity system as a whole.

1.1 Implications of the de-rating process

When introduced in electricity markets, capacity mechanisms become the main entry point to the power sector. Although investors could still install new generation facilities without signing a capacity contract, they are likely to be eager to benefit from this complementary source of remuneration. The de-rating criteria defined by the regulator condition the amount of firm capacity that each resource or technology can trade. De-rating factors should reflect the expected contribution of each resource to reliability and should be based on forecasts on the future operation of the power sector [21][22][23][24][25][26].

This can create a sort of *catch-22* situation, in which the regulator, when forecasting the operation of different resources in order to calculate de-rating factors, is inevitably influencing the expansion of the system and, therefore, also the future reliability performance of each resource. On the one hand, we may have a self-fulfilling prophecy[2], i.e., a situation in which the de-rating factors determined by the regulator drive the system right in the direction outlined by the forecasts on which their calculation is based and allowing it to comply with the reliability target originally defined. On the other hand, there is the risk of a self-destroying prophecy, where de-rating factors drive the system right in the opposite direction than the forecasts behind their computation, therefore shifting the resource mix towards inefficient solutions [12].

1.2 Research gap and objectives of the article

Capacity mechanisms and their impact on the power sector have already been analysed in the academic literature through simulation models. Duggan (2020) [27] presents a detailed review of these theoretical exercises. In many cases, simulation models have been used to assess the impact of capacity mechanisms on system reliability [28][29][30], to compare different designs among them (e.g., strategic reserves vs. centralised capacity markets) [31][32][33], or to compare capacity mechanisms with other regulatory approaches (as energy-only markets or scarcity pricing) [34][35]. Other studies model capacity mechanisms to analyse how they influence the investment decisions of certain market agents [36][37]. In other cases, researchers have tried to model real capacity mechanisms, as Kraft did for the French decentralised capacity market [38]. Simulation models have also been

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[2] In this article, the expression self-fulfilling prophecy is not used with a negative meaning, but rather it refers to a situation in which a prediction causes itself to become true. Of course, this sociological/psychological notion is not used in this article in a strict sense.

widely used to study the cross-border effects of capacity mechanisms [39][40][41][42]. Finally, some simulation models replicate the functioning of capacity mechanisms to study the effect of a specific design element, such as the demand in the auction, the design of the reliability product, or the presence of performance incentives [43][44][45].

De-rating factors used in capacity mechanisms have been rarely addressed by simulation models. Botero et al. (2010) quantitatively studied how the de-rating factor of Colombian wind power varies when applying a set of different de-rating methodologies [46]. Nolan et al. (2017) uses a simulation model to compute the capacity value of demand resources [47]. Bothwell and Hobbs (2017) quantified the loss of economic efficiency that may be provoked by an inaccurate capacity crediting of wind power in ERCOT [12].

This article addresses a similar research question, i.e., the influence of de-rating factors on the outcomes of the capacity market, but focusing on how the de-rating factors affect the reliability of the system and the actual contribution of each resource as compared to the expected one. In particular, this exercise is carried out for solar PV by studying how the de-rating factor that is defined ex-ante, i.e., before the capacity market is cleared, conditions the results of the capacity auction and, consequently, what is the real contribution of solar PV to reliability and whether there is a risk of producing a mismatch between the expectations and the outcomes. This technology has been selected because the effect is more evident for solar PV, but the same findings can be applied to other technologies, e.g., to wind power.

A two-step model is used to simulate the energy and the capacity market. The de-rating factors of the potential new entrants in the mix are considered as exogenous variables defined by the regulator, and the outcome of the model is studied for a range of different values that these parameters can assume. This model is described in detail in section 2, while section 3 presents the results of the simulation model and discusses them. Section 4 concludes and provides the main policy implications of this study.

2 MATERIALS AND METHODS

The analysis presented in this article is based on a two-step model that replicates the participants' behaviour in a capacity auction, in which the bids are based on the results of a simulated future short-term market.

The simulation model is based on the one presented in Mastropietro et al. (2016) [45], which has been adapted to illustrate the influence of de-rating factors on the results of a capacity auction. The model mimics the market agents' auction bids building process: they estimate what their future income in the short-term market will be, and then, on that basis, they evaluate the income they need to get from the capacity remuneration to make the investment decision sufficiently profitable. The ultimate objective is to illustrate how the ex-ante allocation of the firm capacities heavily conditions the outcomes and how the latter might not necessarily match the expectations.

A direct-search approach is applied by means of a two-step model that seeks to attain the least-cost capacity market result, in which agents are able to perfectly anticipate the future mix (and therefore the result of the auction):

- In the first step, all potentially feasible future generation mixes are identified, and the future performance of the short-term market is simulated for each of them, allowing to evaluate the income to be collected by the different resources. This step consists of a centralised deterministic Unit Commitment (UC) that aims at simulating a fully competitive short-term market through minimization of electricity supply costs.

- Then, the second step consists of clearing the capacity auction. To do so, the bids for the capacity market are first calculated based on the result of the short-term market and the de-rating factors. Based on those bids, the capacity market is cleared following a pay-as-cleared mechanism. Finally, the mix resulting from the auction is compared to the initial mix used to simulate the short-term market for validation. Only those generation mixes for which the mix resulting from the auction matches the forecasted one are considered as valid.

- Finally, once all valid solutions are identified, the model selects the one that minimizes the price in the auction.

The second step of the previous model is executed for several different values of the de-rating factor for the solar PV technology. The simulations allow us to analyse the impact that the definition of de-rating factors has on the results of the capacity auction and, consequently, on the evolution of the generation mix.

The model methodology is graphically represented in Figure 1, while the remainder of this section describes in detail the modelling of the two different steps.

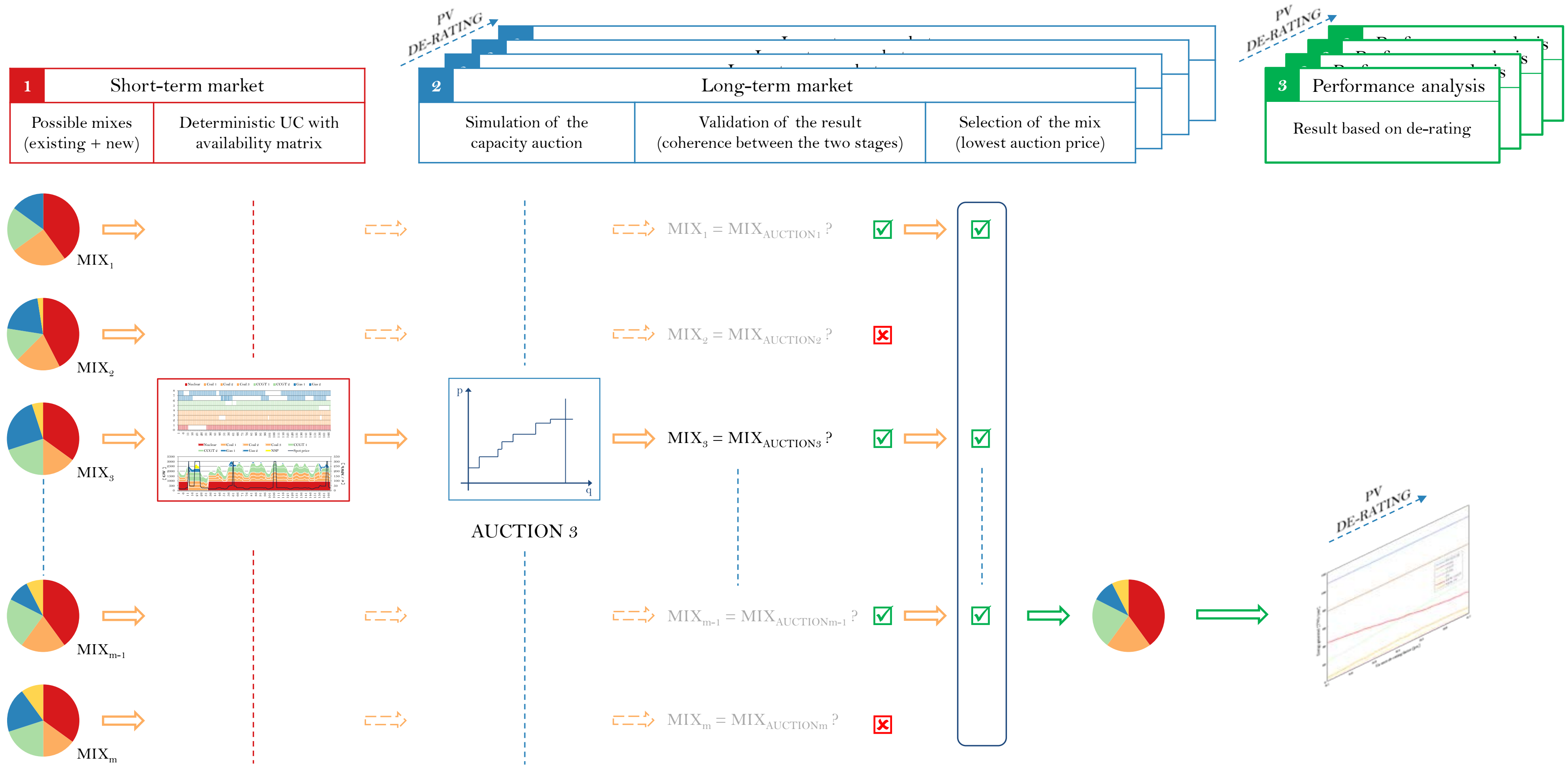

Figure 1: Schematic representation of the model that simulates the capacity auction for different PV de-rating factors

2.1 First step: the short-term market

The first step is the creation of the different scenarios of the future generation mix that feed agents' calculations to determine their bid in the capacity auction. Generation mixes are based on a predefined set of existing generation units (representing a capacity-constrained system dominated by thermal power plants), which are kept constant in all scenarios, and all plausible combinations of new entrants[3]. For the sake of simplicity, the case example only considers two potential technologies for new investments, namely Combined Cycle Gas Turbines (CCGT) and solar photovoltaic (PV) power plants.

For each scenario of the generation mix, a deterministic unit commitment is run for a time horizon of one year, as represented on the left side of Figure 1. This UC reproduces a centralised hourly day-ahead market with perfect competition, inelastic demand and the objective function minimizes electricity supply costs. In order to maintain computation time in an acceptable range, units of the same technology have been clustered, as performed in Mastropietro et al. (2016) [45], which was also proposed in [48], and a Relaxed Mixed Integer Programme (RMIP) solver is used. The revenues of market agents are based on the hourly marginal spot price, plus non-linear side payments [49][50] with daily settlements for those units that do not recover their start-up, no-load or shut-down costs.

Thermal power plants in the model are subject to outages. As in [45], these events are represented through a vector (one per plant) that determines the hourly availability for each

[3] Generation mixes are built considering all possible combinations of new entrants, with the number of new PV units and new CCGT units varying from zero to the maximum number of units of these technologies as expressed in the input data.

thermal power plant and period in the model. These availability vectors are built considering the equivalent forced outage rate (EFOR) of each thermal plant (both existing and new entrants) and are computed by applying a two-state Markov chain with a Monte Carlo approach[4].

PV power plants are considered not to suffer any outage, and their hourly power output is purely deterministic[5], modelled through a load profile that replicates the typical meteorological year. Such hourly load profile has been obtained from the System Advisor Model (SAM) of the National Renewable Energy Laboratory (NREL) [51]. The annualised investment costs for new CCGT and new PV generation units have been obtained from [52] and [53], respectively, considering a discount factor of 7% and a payback period of 20 years. The cost of non-served energy, in this case, is the same as the model price cap, which is set at 3000 €/MWh, which is the price cap established in the EUPHEMIA algorithm used to clear the European regional day-ahead market. The detailed formulation of the UC model is presented hereunder.

[4] For details on the modeling of the availability of thermal plants, please refer to [45].

[5] This is of course a simplification and more precise results may be obtained through a probabilistic modelling of the availability of solar PV, which could result in a reduction of solar PV availability during scarcity conditions. This technology is characterised by a significant variability along the year; however, during the summer period, coincident with peak demand, solar output tends to be high and stable according to the typical meteorological year data used. This should reduce the divergence between a deterministic and a probabilistic modelling of its availability.

Unit Commitment formulation

Indexes and sets

$g \in G$ Generating technologies

$t \in T$ Hourly periods

Parameters

C_g^{LV} Linear variable cost of a unit of technology g [€/MWh]

C_g^{NL} No-load cost of a unit of technology g [€/MWh]

C_g^{SD} Shut-down cost of a unit of technology g [€]

C_g^{SU} Start-up cost of a unit of technology g [€]

C^{NSE} Non-served energy price (in this case 3000 €/MWh) [€/MWh]

$\overline{P}_g$ Maximum power output of a unit of technology g [MW]

$\underline{P}_g$ Minimum power output of a unit of technology g [MW]

N_g Number of units installed of technology g

$AV_{g,t}$ Number of units of technology g available in period t

AIC_g Annualised investment cost of units of technology g [k€/MW]

D_t Demand in period t [MWh]

$\overline{EFOR}_g$ Maximum equivalent forced outage rate of a unit of technology g [p.u.]

$\underline{EFOR}_g$ Minimum equivalent forced outage rate of a unit of technology g [p.u.]

MTR_g Mean time for recovery for units of technology g [periods]

Variables

nse_t Non-served energy in period t [MWh]

$p_{g,t}$ Power output above minimum output of all technology g units in period t [MW]

$u_{g,t}$ Number of units of technology g committed in period t

$v_{g,t}$ Number of units of technology g starting-up in period t

$w_{g,t}$ Number of units of technology g shutting-down in period t

$nse_t, p_{g,t} \in \mathrm{R}$

$u_{g,t}, v_{g,t}, w_{g,t} \in \mathrm{Z}$

Formulation

$$\min \sum_{t \in T} \left[\sum_{g \in G} \left[C_g^{NL} u_{g,t} + C_g^{LV} \left(\underline{P}_g u_{g,t} + p_{g,t} \right) + C_g^{SU} v_{g,t} + C_g^{SD} w_{g,t} \right] + C^{NSE} nse_t \right] \quad (1)$$

$$\sum_{g \in G} \left[\underline{P}_g u_{g,t} + p_{g,t} \right] = D_t - nse_t \qquad \forall t \in T \quad (2)$$

$$u_{g,t} - u_{g,t-1} = v_{g,t} - w_{g,t} \qquad \forall g \in G, \forall t \in T \quad (3)$$

$$p_{g,t} \leq \left(\overline{P}_g - \underline{P}_g \right) u_{g,t} \qquad \forall g \in G, \forall t \in T \quad (4)$$

$$u_{g,t} \leq AV_{g,t} \qquad \forall g \in G, \forall t \in T \quad (5)$$

$$0 \leq u_{g,t}, v_{g,t}, w_{g,t} \leq N_g \qquad \forall g \in G, \forall t \in T \quad (6)$$

$$p_{g,t}, nse_t \geq 0 \qquad \forall g \in G, \forall t \in T \quad (7)$$

Input data

The data used in this modelling exercise are not meant to be realistic and may not reflect the reality of some of the technologies included in the mix.

	Nuclear	Coal	CCGT	Fuel oil	PV	New CCGT	New PV
No. of units	25	20	35	10	5	75	65
$\overline{P}_g$ [MW]	500	500	500	500	200	100	100
$\underline{P}_g$ [MW]	500	300	200	200	0	20	0
C_g^{LV} [€/MWh]	6.5	37.25	60.75	189.5	0	59	0
C_g^{NL} [€/MWh]	0	525	3150	6750	0	1575	0
C_g^{SD} [€]	50	2250	3500	750	0	700	0
C_g^{SU} [€]	50	22500	35000	7500	0	7000	0
$\overline{EFOR}_g$ [p.u.]	0.02	0.15	0.06	0.20	0.00	0.02	0.00
$\underline{EFOR}_g$ [p.u.]	0.01	0.05	0.04	0.10	0.00	0.02	0.00
AIC_g [k€/MW]	-	-	-	-	-	75	135
MTR_g [h]	10	10	10	10	10	10	10

2.2 Second step: the capacity auction

Once the expected incomes from the short-term market are computed for each generating unit, their bids, expressed as €/MW-year, are computed based on the methodology presented in this subsection, the auction is cleared at the marginal price, and all units are remunerated at the price offered by the last accepted bid. De-rated capacities from different technologies compete on equal terms to cover the demand of firm capacity in the auction.

The reliability product for this case study does not consider any performance incentive or penalty[6]. Therefore, bids presented by different agents only depend on the value of investment costs that are not recovered through the short-term market revenues (perfect information on the future behaviour of the market is considered). In the case of existing

[6] Performance incentives are a pivotal element of the design of capacity mechanisms. However, the penalty would not have an impact on the effect which this paper is focusing on; therefore, it is not modeled here.

generators, investment costs are sunk, so their bids are set at zero price. On the other hand, the bids from new entrants can be represented by the following expression [45]:

$$bid_i = \mathrm{Max}\left[0; \frac{icos_i + ocos_i - mrev_i}{capn_i \cdot drf_i}\right]$$

Being these the terms:

bid_i is the bid of generating unit *i*.

$icos_i$ is the annualised investment cost of generating unit *i*.

$ocos_i$ is the total operation cost of generating unit *i* throughout the year.

$mrev_i$ is the total short-term market revenue of generating unit *i* throughout the year.

$capn_i$ is the nameplate capacity of generating unit *i*.

drf_i is the de-rating factor of generating unit *i*

The numerator represents the sum of all costs, investments plus operational costs, minus the revenues from the short-term market. The denominator represents the firm capacity of the power plant, which depends on the de-rating factor assigned by the regulator to each generation unit or each technology.

In this model, the de-rating factor used in the second step is an exogenous variable[7]. For the sake of simplicity, and in order to focus only on the effect that is being studied, the de-rating factors for thermal generators are set according to the EFOR of their technology and do not vary. In contrast, the de-rating factor for PV power plants varies between 10% to

[7] The methodology for the calculation of de-rating factors is a very relevant area in the design of modern capacity markets. No theoretical discussion is provided here, since the topic exceeds the scope of this article, but relevant reviews can be found in [54] or [19].

70%[8]. The goal is to analyse the impact that the regulatory decision regarding the de-rating factor of solar energy may have on the outcome of the capacity auction and the resulting generation mix.

For each value of the PV de-rating factor, the auction is cleared for all the mixes initially considered, using the results of the unit commitment as an input for the bid calculation. Then the mix resulting from the auction is compared to the initial mix and only the mixes where the expectations match the auction results are considered valid solutions from the second step (right side of Figure 1). This validation phase eliminates all infeasible and incoherent mixes, i.e., scenarios in which some of the new resources considered in the unit commitment are eventually not cleared in the auction and, therefore, would not be installed. Finally, among all feasible mixes, the model selects the one with the lowest auction price. Since the model is run for several PV de-rating factors ranging from 10% to 70%, a different optimal mix will be identified for each PV de-rating factor and this allows to study the impact of this pivotal element of the capacity market, as discussed in section 3.

2.3 Initial data for simulations

The existing installed capacity of the power system considered in the simulations is 46 GW, with a preponderance of CCGTs, nuclear and coal power plants, and a small installed capacity of renewable energy sources (namely PV power plants). The system demand is represented as a continuous profile of 8760 hours with an annual peak demand of 44.35 GW in summer, while demand is lower in winter. Three instances of daily demand profiles (low,

[8] In real capacity mechanisms, the de-rating assigned to solar PV may vary between 5% (e.g., Ireland) and 50% (e.g., MISO), as analysed in [14].

medium and high) are shown in Figure 2, together with a graphical representation of the generation mix.

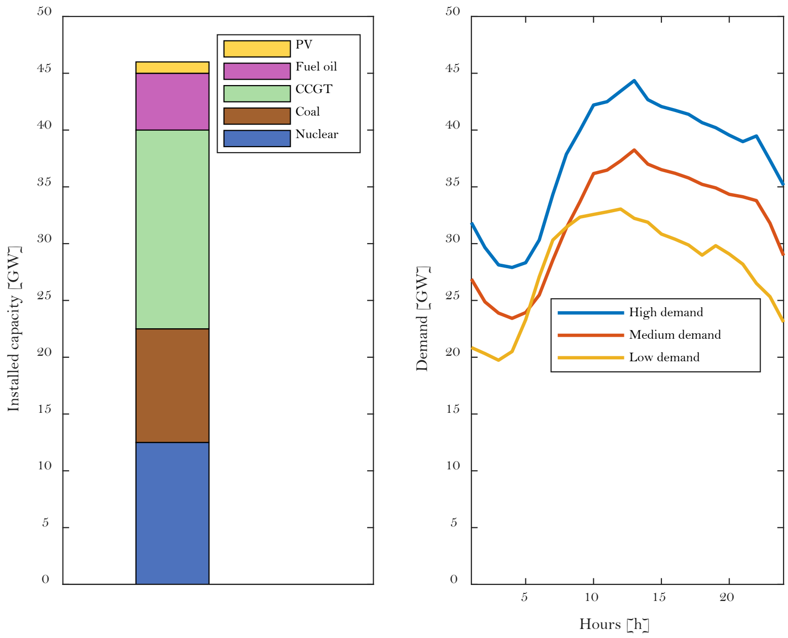

Figure 2: Pre-existing installed capacity (left) and daily demand representation (right)

In this case study, the demand of firm capacity in the capacity auction is another exogenous variable and it is set at 49 GW. This value may reflect the will of the regulator to improve the reliability in the system with respect to the current level and it has been selected to leave some space for new entrants[9], who will determine the price in the capacity auction.

[9] The demand in the auction (or, using different terminologies, the capacity requirement or the target volume) is another central element in the design of capacity mechanisms; it should be set considering the reliability target that the regulator wants to achieve. A theoretical discussion on the topic exceeds the scope of this article, but it can be found in [54] or [55].

3 RESULTS AND DISCUSSIONS: THE ROLE OF THE DE-RATING FACTOR

This section presents the main results that have been extracted from the simulation model. The main focus is on how the resource mix evolves for different values of the PV de-rating factor, analysing several elements, such as the new installed capacity (CCGTs and solar PV) cleared in the auction, the annual production of different technologies, the actual PV de-rating factor that is registered ex post, the non-served energy, the price of the short-term market, and the clearing price of the capacity auction.

3.1 Installed capacity of new entrants

The mix under study needs new firm capacity to meet future demand reliably. Two technologies are competing in the auction, new PV power plants and new CCGTs. In this case example, when the de-rating factor that is recognised to PV units increases, the PV installed capacity in the resource mix increments to the detriment of new CCGTs. The variation of the installed capacity of new PV power plants and new CCGTs as a function of the de-rating factor is represented on the left of Figure 3. The graph on the right of Figure

3 represents the combined firm capacity of PV, new CCGT and new PV, obtained as the product of the de-rating factor and the installed capacity of each of these technologies.

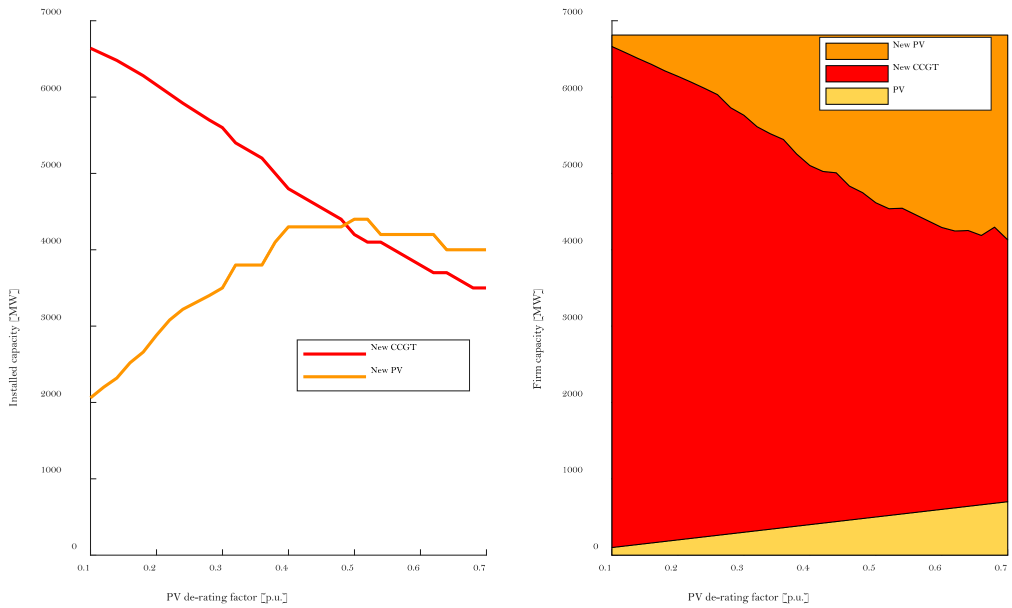

Figure 3: Variation of resulting installed nameplate capacity of new entrants depending on the PV de-rating factor (left) and variation of the firm capacity (right); demand for firm capacity is 49 GW, of which 6.8 GW have to come from new CCGT and solar PV.

Despite this general positive correlation between the PV de-rating factor and its installed capacity in the optimal mix, when the de-rating factor of PV increases up to 0.5, the resulting installed capacity begins to decline. The decrease is caused by the reduction in the installed nameplate capacity of PV needed to cover the auction demand as the de-rating factor grows larger. On the other hand, there is a counterintuitive outcome for those small intervals in which the new PV installed capacity remains constant while the CCGT installed capacity decreases. In those intervals, CCGTs, whose de-rating is fixed, cover a particular share of the demand for firm capacity, while the rest must be covered through PV power plants. If the latter are recognised a higher de-rating factor, a lower CCGT installed capacity will be needed to provide the same amount of firm capacity. All these effects can be better understood by comparing the left and right graphs of Figure 3.

3.2 Annual production

The annual production of each technology is obviously influenced by the outcomes of the capacity auction. As analysed in the previous subsection, higher values of the PV de-rating factor provide a competitive advantage in the auction to new PV units, which increase their installed capacity and their yearly generation, while new CCGTs suffer the opposite effect, i.e., lower capacity cleared in the auction and, consequently, lower annual production.

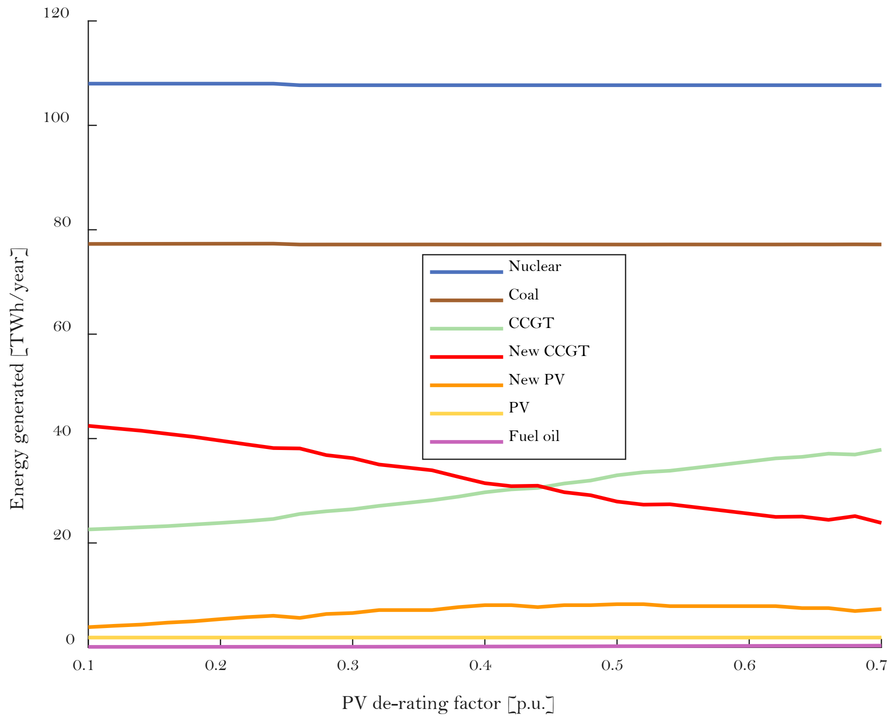

Figure 4: Variation of technology production depending on the PV de-rating factor

However, new PV plants are not able to produce throughout the whole day; therefore, the annual production that is provided by new CCGTs for low PV de-rating factors has to be substituted by existing technologies with higher variable costs (in this case example, existing CCGTs and fuel oil power plants). Since, in the model, existing CCGTs have lower unitary operating costs than fuel oil power plants, except for start-up and shut-down costs, the former experience most of the increase in the annual production (green line) to cover the reduced production by new CCGTs (red line).

3.3 Actual PV contribution to reliability and divergence with its de-rating

As explained in the introduction, the firm capacity of a resource, as calculated through the corresponding de-rating factor, must reflect its expected contribution during scarcity conditions. Therefore, if the objective is to compare the expected contribution with the actual one, the performance of solar PV during scarcity conditions in the modelled power system must be studied.

There are several metrics that can be used to represent reliability and identify scarcity conditions [56][57][58]. As discussed in [19], the growth in the elasticity of demand will not allow in the future the identification of scarcity conditions using only technical parameters and reliability metrics will have to internalise the price dimension in order to be resilient. In this case study, scarcity conditions are identified through the market price, which is used as a critical period indicator, following a basic feature of the reliability options design [24][59][60][59]. A price threshold equal to 300 €/MWh is set and scarcity conditions are defined as those instances when the short-term market price exceeds such threshold[10]. Therefore, the actual contribution of each technology to reliability is

[10] It must be remarked that analogous conclusions could be extracted from the case study presented in this article if the contribution to the system reliability were assessed through a different metric, for instance, by identifying scarcity conditions as those hours with non-served energy and assessing the contribution of each generating unit in those hours (Figure 8 shows how the two metrics present the same behaviour for growing PV de-rating factors).

represented as its average production during scarcity conditions, divided by the total installed capacity of that technology.

As already observed in this case example, low values of the PV de-rating factor lead to low capacity additions of PV. For low penetrations of solar PV, the peak net demand (defined as total system demand minus solar PV production) still occurs in the central hours of the day, causing higher short-term market prices in these hours (Figure 5). In this case, PV power plants provide a valuable contribution to reliability, since they produce when the system is tight.

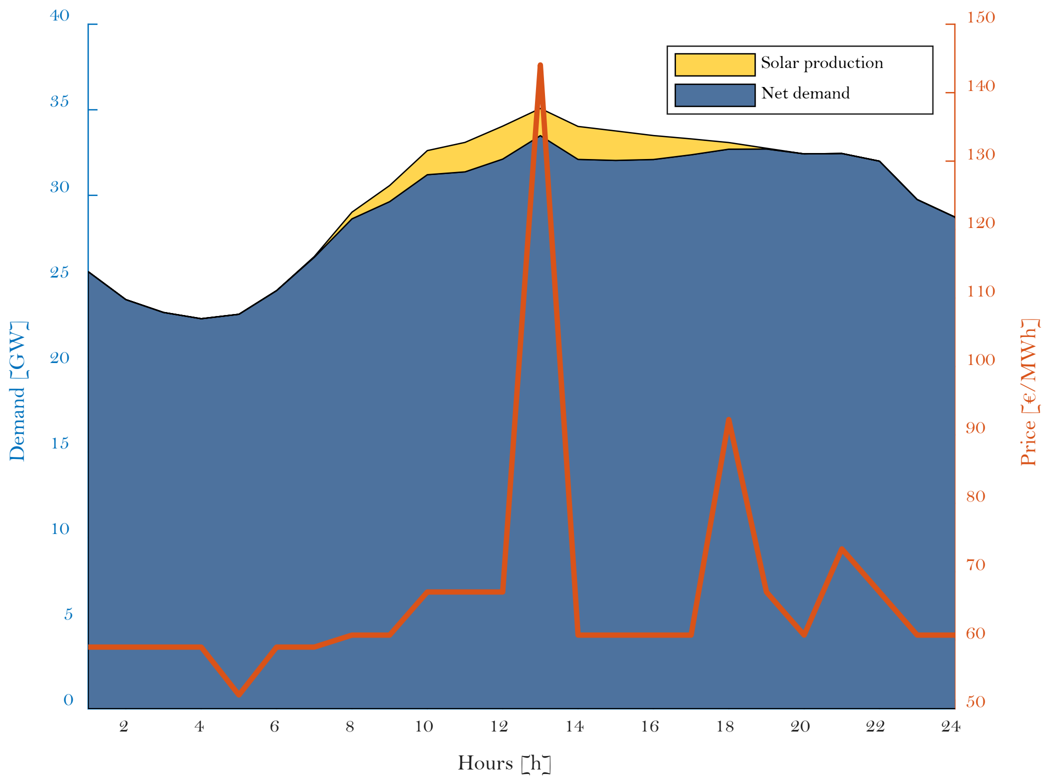

Figure 5: Total demand, net demand, and short-term market price for a PV de-rating factor of 0.1

On the other hand, higher PV de-rating factors increase the new PV capacity cleared in the auction. A higher PV installed capacity provokes a shift in the peak net demand towards the evening, when solar generation declines and thermal power plants are called to ramp up, thus resulting in higher short-term prices and higher risk of scarcity in a time period when solar PV cannot produce (Figure 6). In these conditions, the contribution to reliability from PV power plants is reduced.

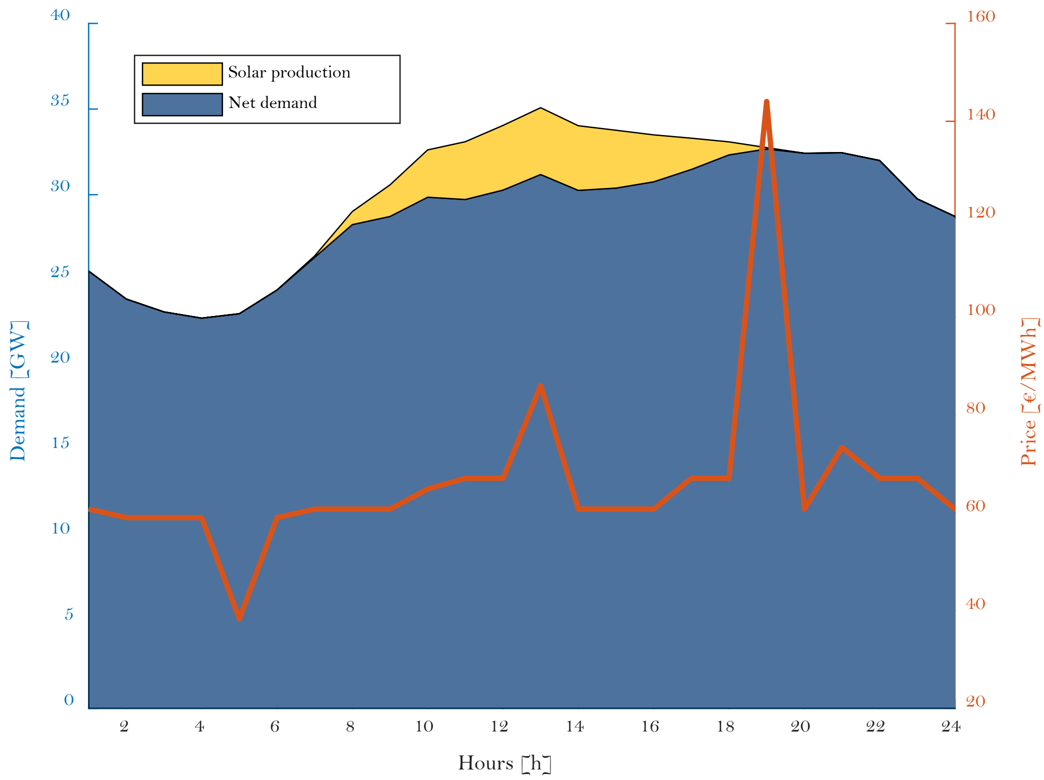

Figure 6: Total demand, net demand, and short-term market price for a PV de-rating factor of 0.7

These changes in the operation of the system, in terms of peak net demand and short-term price, affect the actual contribution to reliability from PV power plants. For higher PV penetrations, these plants will not be able to produce when the system is tight and the short-term price is abnormally high. Therefore their actual contribution will be lower, as shown in Figure 7.

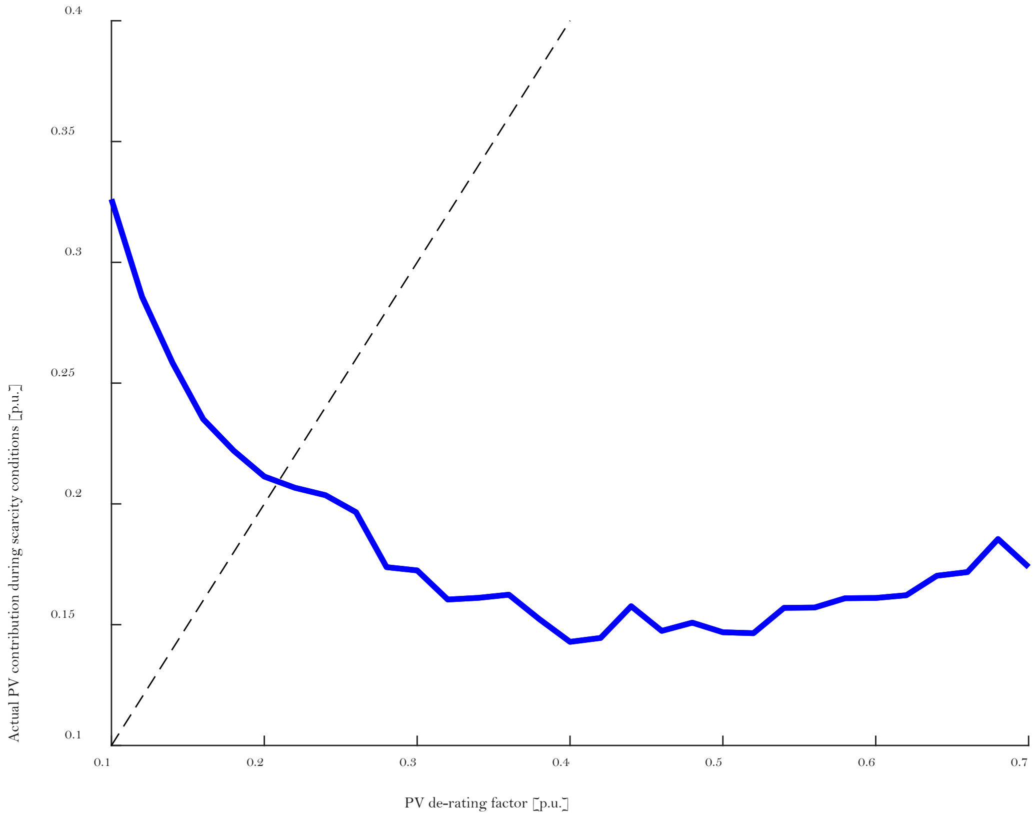

Figure 7: Variation of the actual contribution to reliability from solar PV depending on its de-rating factor[11]

This chart presents a key outcome of our discussion. On the top-left of this line, the actual contribution from PV is higher than the one recognised ex-ante through the de-rating factor assigned by the regulator. Thus, the technology ends up providing a larger contribution than the one it is being remunerated for, based on the original allocation of firm capacity. In this case, an excessive amount of firm capacity from new CCGTs will be procured in the auction, increasing the cost of the capacity mechanism.

[11] The dotted line in Figure 7 represents points in which the actual contribution to reliability from PV matches the PV de-rating factor defined by the regulator.

On the bottom-right of the chart, the actual contribution from PV ends up being lower than the one recognised in the de-rating phase, meaning that the PV technology does not provide the reliability contribution it was remunerated for in the auction. This result also implies that the demand for reliability cannot be expected to be covered, leading to undesired levels of non-served energy (subsection3.4) and short-term market prices (subsection 3.5).

The discrepancy between the assumptions behind the model used to compute de-rating factors (or the demand for firm capacity in the auction) and the actual performance of the resource mix resulting from the auction itself is one of the main challenges in the design of capacity mechanisms. The ideal solution would be to clear capacity markets through an iterative process that allows to validate the outcome of the auction only if such discrepancy is below a certain tolerance, as also proposed in [54]. However, no capacity mechanism implemented to date is based on an iterative process of this type. Therefore, the model presented in this article is based on a conventional clearing of the capacity auction, but it tries to highlight the importance of carefully defining the assumption on which de-rating factors are computed.

3.4 Reliability and scarcity conditions

The PV de-rating factor also influences the overall reliability of the system. As mentioned in the previous subsection, if the de-rating factor of PV power plants is larger than the real reliability contribution that these units provide, the demand for reliability is not satisfied, since many new CCGTs were pushed out of the auction by new PV power plants. This effect can be observed through different reliability metrics. The left chart in Figure 8 shows how the non-served energy registered in the system increases for growing values of PV de-rating factor. A similar increase can be observed in the number of hours with high short-term market prices, which is the reliability metric used to assess the actual contribution to reliability by PV units, as presented in the right chart in Figure 8.

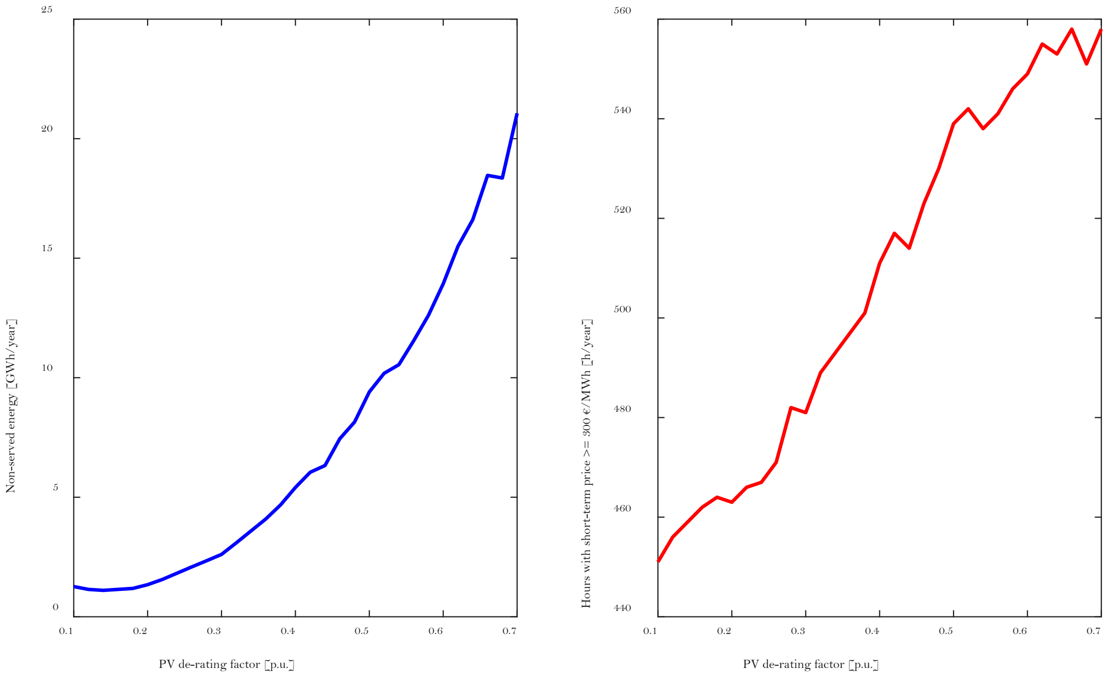

Figure 8: Variation of the non-served energy and the number of hours with high short-term prices

3.5 Short-term prices in the long-term and capacity market prices

3.5.1 Short-term market price

The short-term market price[12] evolves according to the generation mix and the annual production of different technologies. For higher PV de-rating factor values, the yearly production of new CCGTs decreases in favor of more costly existing thermal plants, which leads to an increase in the average short-term market price. This effect is aggravated by the occurrence of scarcity events with non-served energy, during which the short-term price reaches the administrative price cap (see section 2.1).

[12] The short-term price is obtained as the dual variable associated to the generation-demand balance constraint of the optimization problem, see subsection 2.1 for details.

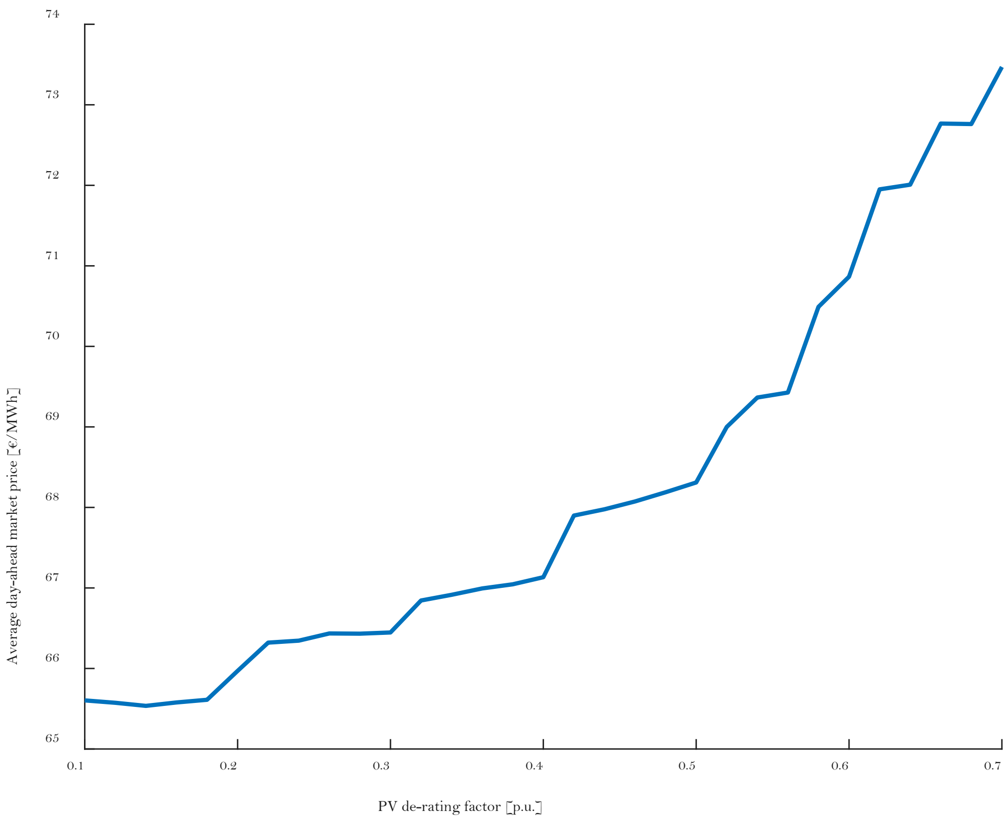

Figure 9: Variation of the average short-term market price depending on the PV de-rating factor

3.5.2 Clearing price of the capacity auction

As explained in subsection 2.2, the bids from generation units in the capacity auction depend on the de-rating factor granted to them and their market revenues in the short-term market. As the de-rating factor of solar PV increases, the bids submitted by these power plants decrease, following the equation introduced in section 2.2. Additionally, the growth in the short-term market price (Figure 9) increases the market revenues for all technologies, thus provoking an overall reduction also in the bids presented by new CCGT units. The variation in the yearly non-recovered investment costs (numerator of the bid calculation formula presented in section 2.2) for solar PV and the bids presented by these new power plants can be observed for two values of the PV de-rating factor in Table 1.

Table 1: Comparison between the yearly non-recovered investment costs and the bids by new PV power plants for a de-rating factor of 0.2 and 0.6

	PV de-rating factor	
	0.2	**0.6**
Non-recovered investment costs [k€/MW]	5.446	4.552
Resulting Bids [k€/MW]	27.232	7.587

The decrease in new PV and new CCGTs bids leads to a reduction in the capacity auction clearing price as the PV de-rating factor rises, which can be observed in Figure 10.

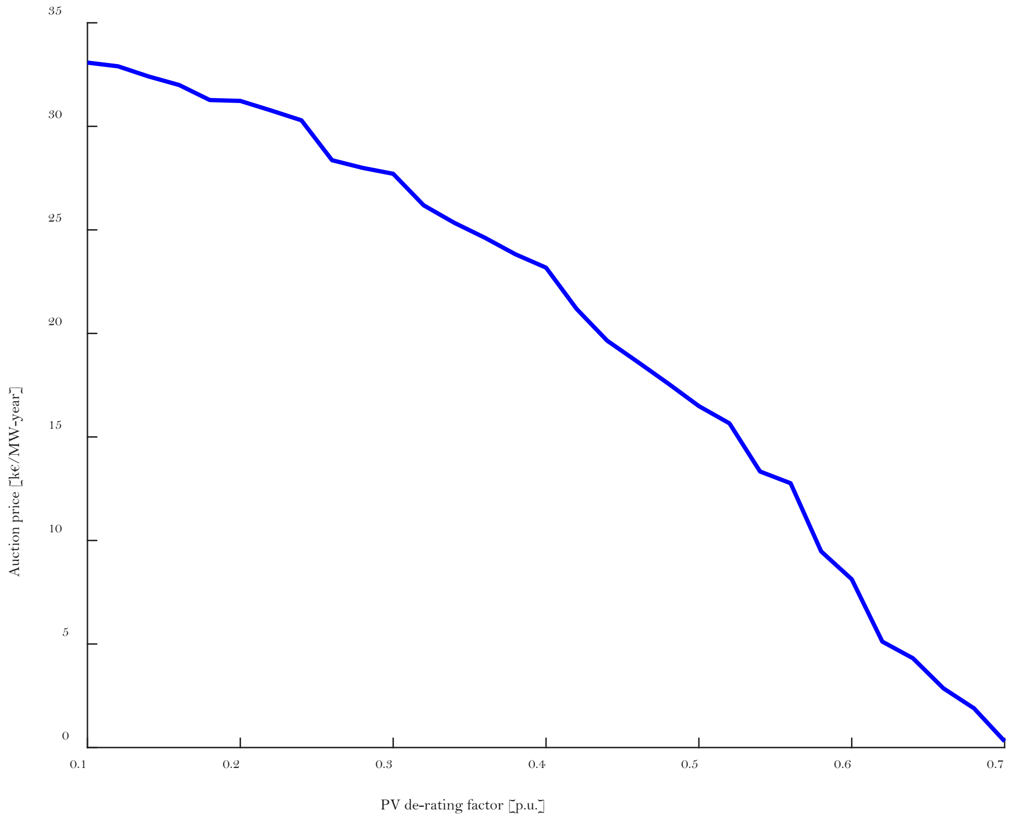

Figure 10: Variation of the capacity auction price depending on the PV de-rating factor

A low clearing price in the capacity auction (due to a generous/optimistic allocation of firm capacity credits) may look like a positive effect since it decreases the overall cost of the capacity mechanism. However, it must be remarked that this might come at the expense of an increase of non-served energy (Figure 8) and the short-term market price (Figure 9). A capacity mechanism cannot be isolated from the rest of the market design and even a small change in an individual parameter, as the de-rating factor of PV units, may significantly impact the outcome of the capacity auction and the performance of the system as a whole.

4 CONCLUSIONS AND POLICY IMPLICATIONS

Capacity mechanisms have become a pillar of the electricity market design while power sectors undergo the energy transition. When they are in place, these mechanisms, together with auctions for renewables, become the main entry point for new resources and their outcome drives the evolution of the entire mix [61]. As presented in this article, a pivotal feature in the design of these instruments is the calculation of the firm capacity that each resource or technology can trade in the capacity market, commonly obtained through the application of de-rating factors.

This paper quantitatively studied the impact of the ex-ante definition of de-rating factors on the resource mix emerging from the capacity market. This analysis is based on a two-step model that simulates the capacity market. The case study presented in this article focuses on a power system dominated by thermal generation, with a summer peak demand, and with only two potential new entrants, i.e., CCGT and solar PV. The de-rating factor assigned to solar PV generation strongly influences the outcome of the capacity market. The larger the PV de-rating factor, the greater the competitive advantage of this technology with respect to CCGTs and the greater the capacity of PV power plants cleared in the auction. The outcome of the auction affects the resource mix and, consequently, the operation and the performance of the system. A larger PV de-rating factor increases solar penetration and this may provoke a shift in the scarcity conditions that the system has to face. However, this also affects the actual contribution of solar PV to reliability. Conversely, an insufficient allocation of firm capacity for solar PV leads to unnecessary extra costs in the capacity auction. These effects, together with the main findings of the article, are represented graphically in Figure 11.

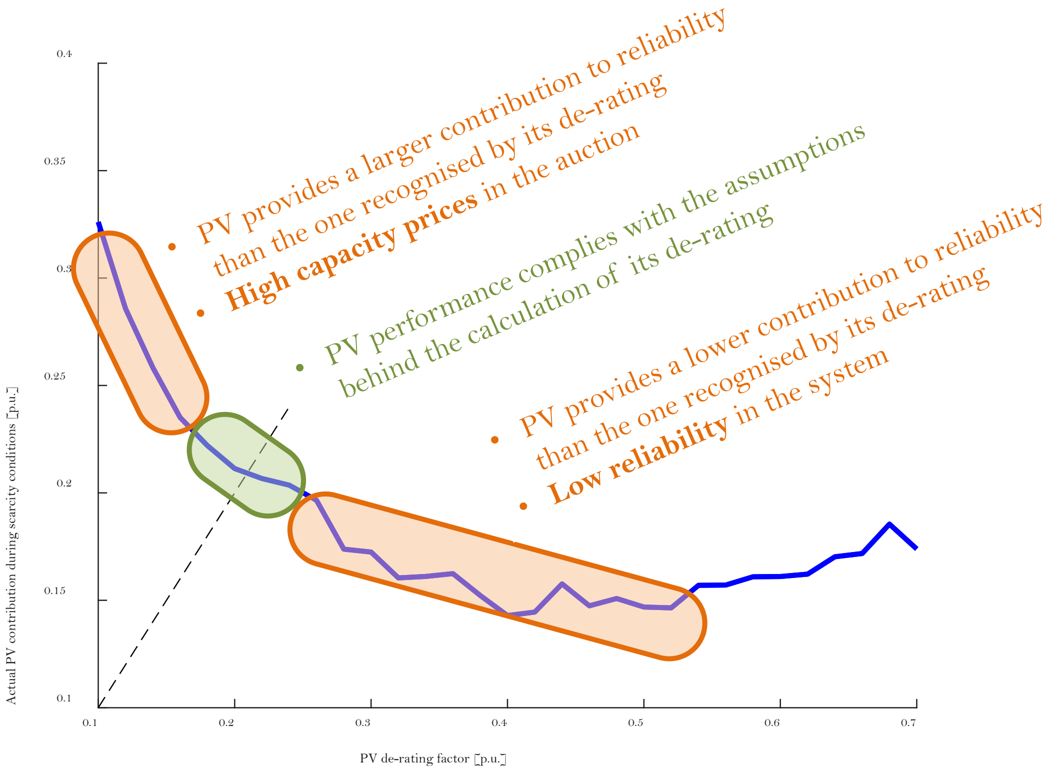

Figure 11. Graphical representation of the main findings of the article

Although the simulation model presented in this article shows these effects for solar PV, its findings also apply to other technologies, especially intermittent resources, whose availability is more likely to present some correlation with demand. With current and upcoming resource mixes, the regulator has a very tight margin to guarantee efficiency when defining a de-rating factor. This decision influences the resource mix and the real contribution that each resource can provide to the system's reliability. If the de-rating factor is too low, it will undercompensate the technology for its reliability contribution and may potentially increase the overall cost of the capacity mechanism. If the de-rating factor is too high, it will distort the outcome of the auction and result in a resource mix that is not able to achieve the reliability target, causing non-served energy and higher short-term market prices.

Capacity mechanisms represent a regulatory intervention that aims at impacting the resource mix to come. However, our discussion reflects the significant complexities that these mechanisms entail, and thus it calls for a careful design process, in which the actual impact of the different design elements needs to be cautiously assessed.

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