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Impact of capacity mechanisms and demand elasticity on generation adequacy with risk-averse generation companies

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ABSTRACT

While on-going and future developments will likely increase the short-term elasticity of the electricity demand, capacity markets are often put forward as a possible remedy to ensure generation adequacy. In this paper, we provide a model formulation of a stochastic non-cooperative capacity planning problem reflecting short-term elastic energy demand, risk-averse investors, and a capacity market. The Conditional-Value-At-Risk is used as a coherent risk-measure. For solving the model, we deploy an Alternating Direction Method of Multipliers. We analyze the impact of short-term demand elasticity on the social welfare, agents' surpluses, and Loss-of-Load-Expectation of an energy-only market and a market complemented by a capacity market. Moreover, we consider the impact of set capacity targets. For the energy-only market, we show that short-term demand elasticity even amplifies the negative effect of risk aversion on social welfare. A capacity market can be used to hedge against the negative effects of risk aversion, even if the capacity target is not set ideally. Furthermore, we show that a capacity market can be used to mitigate welfare transfer to investors and lower the loss-of-load-expectation induced by scarcity times.

1. Introduction

Due to the transition to more sustainable energy, electricity systems are currently facing unprecedented changes and major challenges. More intermittent wind and solar power is incorporated into the system causing more fluctuations in the residual demand. This poses challenges for the system to ensure generation adequacy. In liberalized energy markets, long-term generation adequacy should be the result of investors reacting to market signals. According to economic theory, energy-only markets provide optimal investment incentives through periodic price spikes [1].

However, several factors may cause the investment equilibrium to be different from the social optimum [2]. In order to protect the consumers from price spikes, price caps are implemented. However, price caps are often set lower than the average Value Of Lost Load (VOLL) resulting in a market imperfection. Consequently, expected revenues decrease and investments in capacity decrease, resulting in the so-called "missing money" problem [3].

Another market imperfection is risk-averse behavior. Facing different uncertainties, e.g., in policies, electricity demand, renewable penetration, or fuel prices, investors typically behave risk-averse, i.e., they assign a greater weight to less-beneficial scenarios, which causes sub-optimal investment decisions from a social perspective. Using a stochastic generation expansion model Neuhoff and De Vries [3], and Ehrenmann and Smeers [4] conclude that risk-averse investors construct less capacity than risk-neutral investors resulting in a shift towards less capital intense generation when agents act risk-averse and thus an increased bill of the consumers [3,4]. Petitet et al. [5], and Höschle et al. [6] strengthened these findings by deploying a System Dynamics model and an Alternating Direction Method of Multiplier (ADMM), respectively [5,6].

To ensure generation adequacy capacity markets are subject to on-going discussions. The objective of capacity markets is to counteract the effects of the "missing money" problem and other market imperfections to promote investments by ensuring stable long-term market signals. The goal is to re-establish the market equilibrium of an idealized perfectly competitive energy-only market by providing a payment per-MW of capacity next to the per-MWh revenues obtained from trading energy on the electricity market. In literature, several authors state a need for capacity markets claiming imperfections of the Energy-Only Market (EOM) such as low demand flexibility [7], a failure to

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Nomenclature

Abbreviations

e	Electricity market
cm	Capacity market

Sets

$s \in \mathscr{S}$	Set of scenarios
χ_{gc}	Set of decision variables
$gc \in \mathscr{GC}$	Set of generation companies
$\mathscr{P}$	Set of participant agents ($\mathscr{CO} \cup \mathscr{GC}$)
$co \in \mathscr{CO}$	Set of consumers
$t \in \mathscr{T}$	Set of time steps

Primal variables of participant agents

α	Value at risk (VAR) [€]
$e^{VOLL}_{co,t,s}$	Energy consumption (inelastic part) [MW]
$e^{ela}_{co,t,s}$	Energy consumption (elastic part) [MW]
u	Profit difference between unfavorable scenario and VAR [€]
$e_{gc,t,s}$	Produced electricity [MW]
cm_{gc}	Capacity sold [MW]
y_{gc}	Installed capacity [MW]

Expressions

ANF	Annuity factor [-]
C	Total cost [€]
$l^{c}_{e,t,s}$	Involuntary load curtailment [MW]
CVAR	Condictional-value-at-risk [€]
$\mathbb{E}[\cdot]$	Expected value ($\mathbb{E}(x) = \sum_{s\in\mathscr{S}} p_s x_s$) [·]
WTP^{-1}	Inverse Willingness-To-Pay function [€/MWh]
LOLE	Loss-Of-Load-Expectation [h]
$P^{(2)}$	Penalty term $(\mathrm{MW})^2$
R	Total revenues [€]
S	Surplus [€]
$e_{co,t,s}$	Consumed electricity [MW]
W	Weight of timestep [h]
Π	Weighted expected surplus and CVAR [€]
$\mathbb{W}$	Welfare [€]

Decision variables of Market agents

λ_{cm}	Capacity price [€/MW]
$\lambda_{e,t,s}$	Electricity price [€/MWh]

Parameter

β	risk-aversion factor [-]
C^{FOM}_{gc}	Fixed O&M costs [€/MW]
C^{fuel}_{gc}	Fuel costs [€/MW]
C^{INV}_{gc}	Overnight investment cost [€/MWh]
C^{VOM}_{gc}	Variable O&M cost [€/MWh]
η_{gc}	Efficiency of gc's technology [-]
D^{ela}_{e}	Total elastic share of demand [MW]
D_{cm}	Inelastic capacity demand [MW]
$\overline{D}_{e,t,s}$	Electricity demand cap [MW]
p	Probability [-]
VOLL	Value of loss load [€/MWh]
γ	Weight of expected surplus, $\gamma \in [0, 1]$ [-]

internalize the security-of-supply externalties [8], and, e.g., wholesale energy prices not rising sufficiently to ensure network reliability [9].

Although heavily debated, many authorities assume that the current market design does not attract an adequate amount of capacity investments, and are therefore implementing capacity markets [10]. In the European market design capacity markets are considered as temporary measures to not create undue market distortions [11] are subject to on-going discussions between regulators, investors, and policymakers.

Several studies, such as of Neuhoff and De Vries [3], Ehrenmann and Smeers [4], Petitet et al. [5], Höschle et al. [6], and Mays et al. [12], have already accounted for risk-averse investment behavior in their assessment of complementary capacity markets. These analyses, however, all consider an inelastic demand profile. Despite the commonly applied assumption that electricity demand is for a large share price-inelastic in the short-term (i.e. day-ahead/intraday time-scale), but responsive in the long-term (i.e. investment horizon) [4], on-going developments will likely increase short-term demand elasticity [13,14] and thus, affect the optimal investment in different technologies [15,16]. In theory, increased demand elasticity would affect the system by spreading scarcity rents across more hours, and therefore reducing investment risks. Moreover, demand elasticity would impact the optimal amount of peak-load capacity, and thus also correlates with the ideal capacity target on the capacity market.

The impact of short-term demand elasticity on the performance of capacity markets hence remains undressed. We, therefore, target to fill this literature gap by addressing the question of whether implementing capacity markets still results in a better outcome in terms of generation adequacy and social welfare when considering future elasticity of the energy demand.

Thus, we contribute to the literature in two ways:

1. We formulate a non-cooperative game including capacity markets, short-term demand elasticity, and risk-averse behavior by adapting existing models available in the literature.
2. In a case study, we analyze the role of energy demand elasticity on the performance of an energy-only market, as well as on an energy market complemented with a capacity market, while considering risk-averse investors. Additionally, we assess the impact of a non-ideally set capacity target.

The results reveal policy implications on social welfare, welfare transfer between producers and consumers, and generation adequacy. Consequently, this work is of interest to policymakers, investors, and regulators. Additionally, it can support authorities in the discussion on appropriate capacity markets and targets for generation adequacy.

2. Methodology

We describe a Generation Expansion Planning (GEP) problem as a non-cooperative game. The GEP problem is formulated as an equilibrium problem to reflect the decision-making of individual market participants. We consider Generation Companies (GenCos) and an aggregated consumer as price-taking participants acting on two markets: an hourly-cleared market for electrical energy and a yearly cleared centralized Capacity Market (CM). Each participant is represented by a surplus maximization problem. If no participant has an incentive to deviate from its decisions, given the other agents' decisions, a Nash-equilibrium is found. Agents' decision-making is performed under uncertainty. Each agent's objective is composed of a weighted sum of the expected surplus and Conditional-Value-At-Risk (CVAR) of the surplus. As a coherent risk-measure, the CVAR is well suited for mathematical optimization [17,18]. The CVAR considers the β proportion of scenarios with the worst outcomes. In our case study, all participants are assumed to have a homogeneous attitude towards risk, i.e., all participants have identical β and risk-weight factor.

The surplus is calculated as the difference between revenue and costs. While the consumer perceives the difference between its Willingness-To-Pay (WTP) and its energy and capacity costs as surplus, GenCos gain revenue by selling energy or capacity, while paying for operation and investment.

Knowledge about price levels, elasticity quantities, and the shape of the energy demand curve is sparsely available, particularly when trying to forecast a future situation [19]. Thus, we refrain from modeling demand elasticity as discretely sized quantities to avoid bias in our results towards specific assumptions on price-quantity levels of the demand curve. Instead, we approximate demand elasticity using a linear price-slope that is limited by a price cap. Cross-price elasticities are not considered. The used demand curve representation resembles a simplified version of the work of de Jonghe et al. [20] super-positioning inelastic and elastic demand [20]. An illustration of the inverse willingness-to-pay function (WTP^{-1}) for electrical energy can be found in Fig. 1. D^{ela}_{e} describes the elastic demand volume and is assumed to be constant for each time-step.

In the case study, GenCos can only invest in a single technology. We refrain from using technology portfolios as combining possible technologies in a portfolio would already bias the result. Additionally, using portfolios would lead to internal hedging of risk [21–23]. Instead, by investing in a single technology, GenCos are forced to hedge their risk via the market. The problem is formulated as a greenfield approach using annualized investment costs. Uncertainty is introduced via the scenario-based electrical energy demand ($\overline{D}_{e,t,s}$).

To avoid introducing possible biases towards the outcome by setting the slope of the capacity demand, we assume inelastic demand (D_{cm}) on the capacity market.

2.1. Model formulation

2.1.1. Generation companies

Each GenCo (gc) takes investment decisions (y_{gc}), as well as decision to offer energy ($e_{gc,t,s}$) and capacity (cm_{gc}). Its decision variables are grouped into $\chi_{gc} = \{e_{gc,t,s}, cm_{gc}, y_{gc}, \alpha_{gc}, u_{gc,s} \big| t \in \mathcal{T}, s \in \mathcal{S}\}$.

$$\max_{\chi_{gc}} \Pi_{gc} = \gamma \cdot \mathbb{E}\left[S_{gc}(\chi_{gc})\right] + (1-\gamma)\cdot \mathrm{CVAR}_{gc}(\chi_{gc}), \tag{1a}$$

$$u_{gc,s} \geq \alpha_{gc} - S_{gc,s}(\chi_{gc}), (\delta_{gc,s}), \quad \forall s \in \mathcal{S}, \tag{1b}$$

$$e_{gc,t,s} \leq y_{gc}, \quad (\mu_{gc,k,t,s}), \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{1c}$$

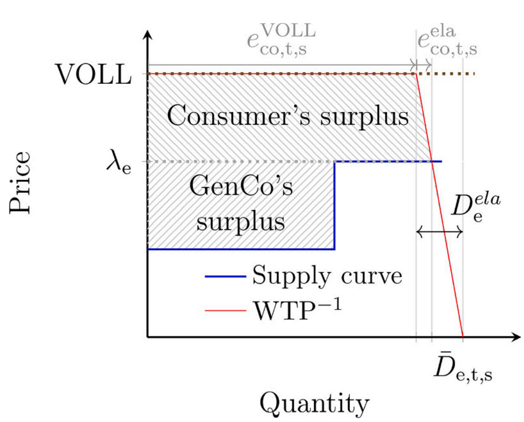

Fig. 1. Illustration of the elastic demand via inverse WTP function. Energy demand is modeled using a linear slope described by the elastic demand (D^{ela}_{e}) and the energy demand at zero cost ($\overline{D}_{e,t,s}$).

$$cm_{gc} \leq y_{gc}, \quad (\nu_{gc}), \tag{1d}$$

$$e_{gc,t,s} \geq 0, \quad \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{1e}$$

$$cm_{gc}, y_{gc}, u_{gc,s} \geq 0, \quad \forall s \in \mathcal{S}, \tag{1f}$$

$$\alpha_{gc} \in \mathbb{R}. \tag{1g}$$

with

$$S_{gc,s}(\chi_{gc}) = R_{gc,s}(\chi_{gc}) - C_{gc,s}(\chi_{gc}), \tag{1h}$$

$$\mathrm{CVAR}_{gc}(\chi_{gc}) = \alpha_{gc} - \frac{1}{\beta}\mathbb{E}\left[u_{gc}\right], \tag{1i}$$

$$R_{gc,s}(\chi_{gc}) = \lambda_{cm}\cdot cm_{gc} + \sum_{t\in\mathcal{T}} \lambda_{e,t,s}\cdot e_{gc,t,s}\cdot \mathrm{W}_t, \tag{1j}$$

$$C_{gc,s}(\chi_{gc}) = \mathrm{ANF}_{gc}\cdot C^{INV}_{gc}\cdot y_{gc} + C^{FOM}_{gc}\cdot y_{gc} + \sum_{t\in\mathcal{T}}\left(C^{VOM}_{gc} + \frac{C^{fuel}_{gc}}{\eta_{gc}}\right)\cdot e_{gc,t,s}\cdot \mathrm{W}_t. \tag{1k}$$

The surplus ($S_{gc,s}$) in each scenario (s) is described as the difference of revenue ($R_{gc,s}$), and costs ($C_{gc,s}$) (Eq. (1h)). Revenue is generated by selling energy and capacity (Eq. (1j)). As described in Eq. (1k), costs are composed of annualized investment costs (INV), Variable Operation and Maintenance costs (VOM), Fixed Operation and Maintenance costs (FOM) and fuel costs (fuel). Annuities of the investment costs (C^{INV}_{gc}) are calculated using the annuity factor (ANF). FOM costs are calculated using C^{FOM}_{gc}. The costs per MWh of electricity are calculated using the VOM costs (C^{VOM}_{gc}) and fuel costs (C^{fuel}_{gc}) divided by the generation efficiency (η_{gc}). W_t reflects the duration of a time-step.

For representing the demand of a whole year, representative days are used, following the methodology of [24]. The mathematical description of the CVAR is taken from [17] using auxiliary decision variables α_{gc}. α_{gc} can be interpreted as the endogenously calculated Value-At-Risk (VAR_β)[1] [4]. The endogenous valuation of scenarios is represented via Eq. (1b). If the profit of a scenario is smaller than α_{gc}, $u_{gc,s}$ is positive and the constraint is binding. Consequently, the dual of the constraint (1b), $\delta_{gc,s}$, can take a value larger than zero. As $\delta_{gc,s}$ can only be positive for scenarios whose utility is below VAR_β, it can be interpreted as the risk-adjusted probability [4]. Eqs. (1c) and (1d) describe capacity constraints limiting the contribution of electrical energy and capacity. Operator $\mathbb{E}[x]$ returns the expected value of input x as $\sum_{s\in\mathcal{S}} p_s\cdot x_s$, with $\sum_{s\in\mathcal{S}} p_s = 1$.

2.1.2. Consumer

The Consumer (co) maximizes the weighted expected surplus and CVAR based on the decision variables $\chi_{co} = \{e^{VOLL}_{co,t,s}, e^{ela}_{co,t,s}, \alpha_{co}, u_{co,s} \big| t \in \mathcal{T}\ s \in \mathcal{S}\}$. Utility through "consumption of capacity" is not considered. The served demand is decomposed in an elastic part and an inelastic part by introducing two auxiliary variables, $e^{VOLL}_{co,t,s}$ and $e^{ela}_{co,t,s}$. Eqs. (2c), (2d), (2i) represent the geometrical interpretation as given in Fig. 1. While the energy demand is considered elastic and curtailment of energy is possible (Eq. (2c)), the capacity demand is considered inelastic and non-curtailable.

[1] More precisely, α describes the most beneficial utility of the outer most scenario of all (endogenously) chosen scenarios with a cumulative probability of β: $VAR_\beta(\chi_{gc}) = \max_{s\in\mathcal{S}}\{S_{gc,s} \big| \sum_{s\in\mathcal{S}} p_s \leq \beta\}$ [6]

$$\max_{\chi_{co}} \quad \Pi_{co} = \gamma \cdot \mathbb{E}[S_{co}(\chi_{co})] + (1-\gamma) \cdot \mathrm{CVAR}_{co}(\chi_{co}), \tag{2a}$$

$$u_{co,s} \geq \alpha_{co} - S_{co,s}(\chi_{co}), \quad (\delta_{co,s}), \quad \forall s \in \mathcal{S}, \tag{2b}$$

$$\overline{D}_{e,t,s} - e^{VOLL}_{co,t,s} - D^{ela}_{e} \geq 0, \left(\rho^{1}_{e,t,s}\right), \quad \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{2c}$$

$$D^{ela}_{e} - e^{ela}_{co,t,s} \geq 0, \qquad \left(\rho^{2}_{e,t,s}\right), \quad \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{2d}$$

$$e^{VOLL}_{co,t,s}, e^{ela}_{co,t,s} \geq 0, \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{2e}$$

$$\alpha_{co} \in \mathbb{R}, \tag{2f}$$

$$u_{co,s} \geq 0, \qquad \forall s \in \mathcal{S}. \tag{2g}$$

with

$$S_{co,s}(\chi_{co}) = R_{co,s}(\chi_{co}) - C_{co,s}(\chi_{co}), \tag{2h}$$

$$R_{co,s}(\chi_{co}) = \sum_{t \in \mathcal{T}} W_t \left[e_{co,t,s} \cdot \mathrm{VOLL} - \left(e^{ela}_{co,t,s}\right)^2 \frac{\mathrm{VOLL}}{D^{ela}_{e} \cdot 2})\right], \tag{2i}$$

$$C_{co,s}(\chi_{co}) = \lambda_{cm} \cdot D_{cm} + \sum_{t \in \mathcal{T}} \lambda_{e,t,s} \cdot e_{co,t,s} \cdot W_t, \tag{2j}$$

$$\mathrm{CVAR}_{co}(\chi_{co}) = \alpha_{co} - \frac{1}{\beta} \mathbb{E}[u_{co}], \tag{2k}$$

$$e_{co,t,s} = e^{VOLL}_{co,t,s} + e^{ela}_{co,t,s}. \tag{2l}$$

The utility of the consumer is the integrated inverse willingness-to-pay of the energy market minus the costs incurred in the energy and the capacity market. The integrated inverse willingness-to-pay of the energy-market can be interpreted as revenue (Eq. (2i)). The costs of the consumer (Eq. (2j)) are the total cost for capacity (product of the capacity price, λ_{cm}, and capacity demand, D_{cm}) and energy (product of served energy, $e_{co,t,s}$, and the energy price, $\lambda_{e,t,s}$).

2.1.3. Markets

Markets provide the price that balances the offered volumes of all agents, i.e., no unilateral change exists that improves the profit of the agents. Formally markets connect GenCos' and the consumer's problem by providing balancing constraints (Eqs. (3a-3b)) that connect the contribution of each agent to the specific market. The formulation of the markets is distributed among the agents, whereby the supply-side is represented by the GenCos, the demand-side by the consumer. Both sides are balanced by the clearing constraints:

$$\sum_{gc \in \mathcal{GC}} e_{gc,t,s} - e_{co,t,s} = 0, \left(\lambda'_{e,t,s}\right), \forall t \in \mathcal{T}, s \in \mathcal{S}, \tag{3a}$$

$$\sum_{gc \in \mathcal{GC}} cm_{gc} - D_{cm} = 0, (\lambda_{cm}) \tag{3b}$$

Eq. (3a) describes the energy balance for all participants, Eq. (3b) the capacity balance of the centralized capacity market. The dual variable of the energy balance can be interpreted as the product of prices and risk-perception: $\lambda_{e,t,s} = \lambda'_{e,t,s} / (W_t \cdot (p_s \gamma + \delta_{i,s}))$. The capacity price is defined as $\lambda_{cm} \in \mathbb{R}$. This capacity price will remain positive in every setting, since the capacity traded at the capacity market can be lower than the installed capacity (Eq. (1d)).

2.2. Solution approach

Generally, multiple solution algorithms are available for non-cooperative games with a Nash-equilibrium. The choice and applicability depend on the properties of the considered equilibrium problem [4,25]. Solution algorithms can be differentiated into three groups. Firstly, equilibrium problems may be solved as MCP reformulation by solving its square set of complementarity constraints using dedicated solvers, e.g., PATH, or via introducing additional so-called big M constraints as proposed in [26]. However, solving large squared sets as a result of models with, e.g., a large number of scenarios can become computationally challenging. Secondly, the considered equilibrium problems may be cast into an optimization problem. Whether an equilibrium problem can be converted into an optimization problem depends on the Symmetry Principle which is related to the symmetry of the Hessian matrix in the optimization. Casting an equilibrium problem into an optimization problem is not always possible [4,25,27]. Lastly, iterative solution techniques, such as the Alternating Direction Method of Multipliers (ADMM) can be used to solve equilibrium problems[2]. ADMM is an iterative solution approach that updates the agents' decision variables sequentially.

The presented problem of the consumer is a convex quadratic problem with quadratic constraints, which may be solved with conventional solvers such as PATH. However, PATH often faces problems for large problem instances.

Instead, ADMM is proposed as the solution algorithm. ADMM provides several advantages, such as scalability and guarantee of convergence to optimality under certain assumptions, e.g. if the corresponding optimization problem exists. In addition, ADMM offers parallel computing possibilities when the problem scales.

The utilized ADMM algorithm is based on [6,28] and depicted in Algorithm 1 resembling the *exchange problem* as proposed in [28].

Equation (4) describes the augmented Lagrangian of agent i, which can be either a GenCo or the consumer. Here, the first term, Π_i, is the agent's objective function being the weighted expected surplus and CVAR as described in problems (1a) and (2a). In contrast with the work of Höschle et al. [6], in this work, we formulate the augmented Lagrangian using scenario-profits to simplify the formulation. Here, Π_i corresponds to the cost function and the first penalty term, which is equivalent to the revenues. The 2nd penalty term resembles the formulation of Höschle et al. [6] taking the market-clearing constraints and the deviation from the last contribution to the markets into account. $\boldsymbol{x}_{gc}$ and $\boldsymbol{x}_{co}$ are concatenated column arrays holding all contribution variables to the energy market and the capacity market. The exponent k indicates the kth iteration, while $k+1$ is the current iteration. $\bar{\boldsymbol{x}}$ describes the mean imbalances and, therefore, takes the residual $\boldsymbol{r}$ and the number of agents $|\mathcal{P}|$ into account. Once an optimum is reached, the market-balances are fulfilled and no agent is incentivized to change its decision. Therefore the 2nd penalty term becomes zero at the equilibrium.

The equilibrium is found via iteration. First, all agents' decisions are updated (Eq. (5)) solving their respective augmented problems (Eq. (4)). Prices are subsequently updated. In the price update step (cf. Eq. (6)) market prices are decreased when the entries of residual $\boldsymbol{r}$ are positive, i.e. if there is overproduction. In case of an underproduction (entries of $\boldsymbol{r}$ are negative) prices are increased. This way the algorithm uses the price to coordinate the generation and consumer side. The algorithm terminates if primal and dual errors fall below defined bounds.

To guarantee coincidence of solutions it can be shown that the KKT conditions of the augmented agents' problems (Eq. (5)) coincide with the corresponding MCP reformulation of the agents' problems (1a-2a) if the ADMM algorithm converged. Thus, solutions of the ADMM algorithm and the equilibrium problem formulation (1a-2a) are identical with respect to the convergence criteria.[3]

In addition to the original formulation, we introduce a weighted 2nd

[2] Convergence of ADMM is proven for problems with objective functions that can be separated [28].

[3] For further information on the coincidence between ADMM solution and the solution of the corresponding equilibrium problem we would like to refer to [29].

Algorithm 1: ADMM algorithm (following [28, 6])

Augmented Lagrangian of agent i:

$$L_{\mathrm{i}}(\rho, \boldsymbol{\chi}_{\mathrm{i}}, \boldsymbol{\chi}_{-\mathrm{i}}, \boldsymbol{\lambda}) = \Pi_{\mathrm{i}}(\boldsymbol{\chi}_{\mathrm{i}}^{k+1}, \boldsymbol{\lambda}^k) - \underbrace{\rho/2||\boldsymbol{x}_{\mathrm{i}}^{k+1} - (\boldsymbol{x}_{\mathrm{i}}^k - \bar{\boldsymbol{x}}^k)||_2}_{2^{nd}\ penalty,\ P^{(2)}} \quad (4)$$

s.t. constraints (1b)-(1g) or (2b)-(2g)

$$\begin{aligned} \textit{with:}\ \boldsymbol{x}_{\mathrm{gc}}^T &= (\mathrm{e}_{\mathrm{gc},\mathrm{t}_1,\mathrm{s}_1}, \dots, \mathrm{e}_{\mathrm{gc},\mathrm{t}_{|\mathcal{T}|},\mathrm{s}_{|\mathcal{S}|}}, cm_{\mathrm{gc}}) \\ \boldsymbol{x}_{\mathrm{co}}^T &= (\mathrm{e}_{\mathrm{co},\mathrm{t}_1,\mathrm{s}_1}, \dots, \mathrm{e}_{\mathrm{co},\mathrm{t}_{|\mathcal{T}|},\mathrm{s}_{|\mathcal{S}|}}, D_{\mathrm{cm}}) \\ \boldsymbol{\lambda}^T &= (\lambda_{\mathrm{e},\mathrm{t}_1,\mathrm{s}_1}, \dots, \lambda_{\mathrm{e},\mathrm{t}_{|\mathcal{T}|},\mathrm{s}_{|\mathcal{S}|}}, \lambda_{\mathrm{cm}}) \\ \boldsymbol{r} &= \sum_{\mathrm{gc}\in\mathcal{GC}} \boldsymbol{x}_{\mathrm{gc}} - \boldsymbol{x}_{\mathrm{co}} \\ \bar{\boldsymbol{x}} &= \boldsymbol{r}/|\mathcal{P}| \end{aligned}$$

Algorithm:

Initialization of agents' problems

repeat

Solve agents' problems:

for i $\in \mathcal{P}$ **do**

$$\boldsymbol{\chi}_{\mathrm{i}}^{k+1} = \underset{\boldsymbol{\chi}_{\mathrm{i}}^{k+1}}{\mathrm{argmax}}\, L_{\mathrm{i}}(\rho, \boldsymbol{\chi}_{\mathrm{i}}^{k+1}, \boldsymbol{\chi}_{-\mathrm{i}}^{k}, \boldsymbol{\lambda}^k) \quad (5)$$

end

Update prices:

$$\boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k - \rho/2 \cdot \boldsymbol{r}^{k+1} \quad (6)$$

until *(primal residual < primal error bound) AND (dual residual < dual error bound);*

Algorithm 1. ADMM algorithm (following [6,28]).

penalty term for the energy market to improve the convergence taking different weights of representative days and risk-averse behavior into account. This heuristic bases on the idea of keeping the algorithm update step reasonably constrained. To ensure this, the penalty terms on decision variables have to reflect the order of magnitude the objective changes if the decision variable changes. In other words, the coefficients of the penalty terms are set to mimic the corresponding coefficients of the decision variables as they impact the objective function. The order of magnitude of the expected dual variables of the linking constraint of a corresponding optimization problem is emulated. For the energy market the 2$^{\mathrm{nd}}$ penalty term is modeled for participant *i* as:

$$P_{\mathrm{e,i}}^{(2)} = \sum_{\mathrm{t}\in\mathcal{T},s\in\mathcal{S}} s_{\mathrm{e,i,t,s}} \cdot \rho \Big/ 2 \cdot \left(e_{\mathrm{i,t,s}}^{k+1} - e_{\mathrm{i,t,s}}^{k} + \bar{x}_{\mathrm{e,t,s}}^{k}\right)^2 \quad (7)$$

$$s_{\mathrm{e,i,t,s}} = \mathrm{W_t} \cdot (p_s\gamma + \delta_{\mathrm{i,s}}) \quad (8)$$

Here, $\bar{x}_{\mathrm{e,t,s}}$ is one entry of the mean residual $\bar{x}$ at timestep t and scenario s.

To validate the convergence and solution tolerance criteria of the ADMM algorithm, we additionally solve the considered problem as an optimization problem for the inelastic demand case. Using a primal and dual error bound of 10^{-4} and an iteration limit of 50000, the maximum relative deviation of the utility between both solution methods was 6.1×10^{-7}% for the inelastic demand case. The absolute utility deviation corresponds to 13.7€. The iteration limit was reached three times resulting in a maximum primal error of 4.497MW.

All other runs, in which demand elasticity is reflected, stay within the error bounds of 10^{-4} for primal and dual error and the iteration limit of 50000.

The optimization routines are implemented in Julia and executed on the Vlaams-Supercomputing-Centrum cluster using two Xeon Gold 6140 CPUs@2.3 GHz (Skylake) processors with in total 36 cores and 192GB of RAM. The calculation of the considered problem instances was conducted in parallel where each instance is solved sequentially (agents' problems are solved sequentially). In total 168 problem instances were solved in this study.

On average each problem needs 1246 iterations to converge (median). The 10% quantile is 742 and the 90% quantile is 10433 iterations. Solving one iteration takes approximately 1.4s on this machine. In our implementation, the GenCo model has a size of 1940 rows and 1943 columns, while the consumer model has a size of model with 1920 rows, 1920 columns.

3. Case study

To answer the question to what extent short-run demand elasticity affects the need for a capacity market with risk-averse participants, we assess the impact of demand elasticity on (i) an energy-only market (EOM) and (ii) an energy market complemented with a capacity market. The economic performance is assessed by introducing metrics for the system perspective, and the agent perspective.

On the system level, the performance is evaluated using the total surplus of all participants, which can be interpreted as social welfare ($\mathbb{W}$).

$$\mathbb{W} = \mathbb{E}\left[\sum_{i\in\mathscr{P}} S_i\right] = \mathbb{E}\left[R_{co} - \sum_{gc\in\mathscr{GC}} C_{gc}\right] \tag{9}$$

Here, $\mathscr{GC}$ describes the set of GenCos and $\mathscr{P}$ the set of all participants (consumer and GenCOs).

On the agent-level, performance is evaluated using the expected Consumer's ($\mathbb{E}[S_{co}]$), and GenCo's surplus ($\mathbb{E}[S_{gc}]$) to describe possible welfare transfers between the agents. Lastly, we assess the hours where supply falls short using the Loss-of-Load-Expectation (LOLE), which formalizes to

$$\mathrm{LOLE} = \sum_{W_{t,s}\in\left\{W_{t,s}\,|\,l^c_{e,t,s}>0\right\}} p_s \cdot W_{t,s}, \tag{10}$$

$$l^c_{e,t,s} = \overline{D}_{e,t,s} - D^{ela}_{e} - e^{VOLL}_{co,t,s}. \tag{11}$$

To identify the dependence of demand elasticity and risk aversion on the system performance, we vary (i) total amount of elastic demand (D^{ela}_e), (ii) participants' attitudes towards risk (β), and (iii) the capacity demand (D_{cm}).

3.1. Definition of input

This study considers investments in base and peak technology. The technical and economic parameters are inspired by Simoes et al. [30] and can be found in Table 1. We implicitly account for renewable energy by taking the residual demand curve as (uncertain) energy demand. The yearly energy demand is described by eight representative days ($\sum_{t\in\mathscr{T}} W_t = 8760$h), resulting in a total of $|\mathscr{T}| = 192$ time steps. The choice and the weight of the representative days are the results of an optimization-based approach following the methodology of [24]. To accurately reflect moments of scarcities, we enforce the optimization to select three peak days with a weight of 1.[4] To preserve computational tractability $|\mathscr{S}| = 10$ scenarios are considered, of which each has a probability of $p_s = 0.1$ and 192 time steps. As the model showed the most sensitivity to the energy demand ($\overline{D}_{e,t,s}$), uncertainty is solely considered in energy demand ($\overline{D}_{e,t,s}$). We apply uncertainty to the energy demand via scaling, e.g. if we assume that the energy demand grows by 1%, we multiply the energy demand profile by 1.01. We assume the demand to uniformly distribute with an interval length of 5%, varying from −2.5% to +2.5%, i.e. each scenario differs from its precursor by an increase in demand of 0.5%. An overview of the utilized energy profiles is given in Fig. 2. In all simulations, participants have a homogeneous attitude towards risk (β), and a weight of $\gamma = 0.1$. The Value-Of-Lost-Load (VOLL) is set at 3000€/MWh.

Table 1
Economical and technical parameters of the considered technologies.

	ANF	C^{INV}	C^{FOM}	C^{VOM}	C^{fuel}	η
	-	k€ /MW	€ /MW	€ /MWh	€ /MWh	-
Base	0.033	850	0.023	6.0	40.0	0.55
Peak	0.033	550	0.03	11.0	40.0	0.38

[4] The taken choice results in an hourly resolution of the 20 hours with the highest demand.

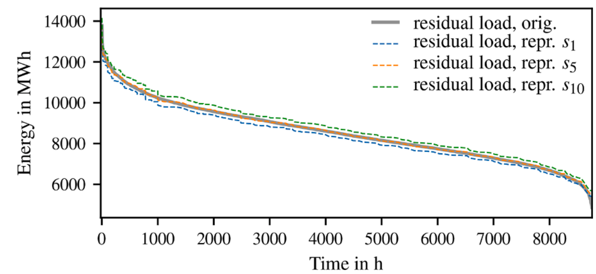

Fig. 2. Overview of utilized residual demand profiles. The low demand scenario is s_1, the high demand scenario s_{10}.

3.2. Impact of short-term demand elasticity on generation mix

Comparing the installed capacities for the **Energy-Only Market (EOM)**, as shown in Fig. 3, we can infer three relations between risk aversion, elastic energy demand, and the generation mix:

1. An increase in demand elasticity (darker to lighter shades) leads to a decrease in total capacity (cf. orange lines vertically). As more demand reacts to spike prices, peak demands are reduced leading to a reduction in peak capacity (dashed lines) while base capacity (dotted lines) hardly changes.
2. Even though demand elasticity increases with constant steps, incremental reductions in peak-capacity decrease with growing demand elasticity (cf. distances between dashed orange lines decrease).
3. Increasing risk aversion (left to right) leads to a decrease in total capacity. As risk-averse participants value less beneficial scenarios higher, less capacity with high investment costs is installed and the generation mix is shifted towards more peak capacity.

In literature each of this results is described individually for the EOM case [6,20,31].

A **capacity market (CM)** that complements an energy market bears the risk of being a market distortion. If the capacity target is not set ideally social welfare could be negatively impacted. We determine the performance of a capacity market with a social optimal set capacity target[5], which is calculated using an ex-ante optimization run considering an EOM with risk-neutral participants. Hence, social welfare is identical in both settings (*EOM*, and *EOM+CM*) for $\beta = 1.0$.

Comparing the capacities depicted (cf. Fig. 3) reveals two differences for the *DA+CM* case comparing to the *EOM* case:

1. The total installed capacity remains constant (solid green shaded lines). If participants are risk-averse then the capacity target becomes binding, i.e., the capacity market clears with a price larger than zero, providing an incentive to invest in capacity in order to reach the capacity target.

[5] Assuming the ideal capacity target is known ex-ante.

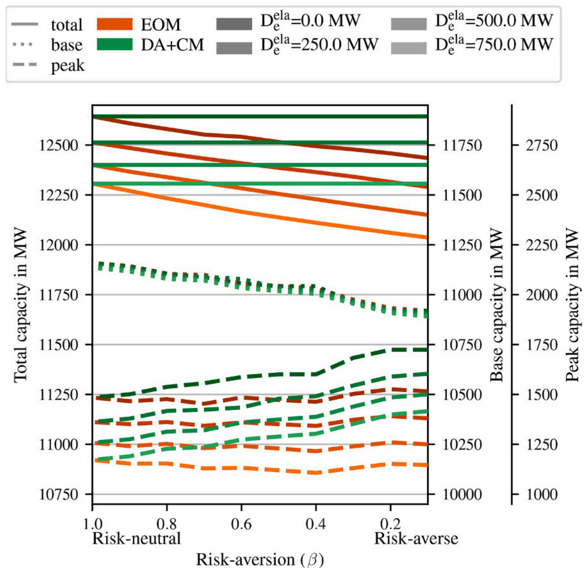

Fig. 3. Impact of risk aversion and elastic demand on installed capacities in an EOM and a setting with complementary CM (DA+CM). Shades of color indicate different amounts of elastic demand.

2. Peak capacity compensates for lower base capacity. The shares in the technology mix shift to peak technology.

Presented results regarding capacity investments confirm and extend previous findings of e.g., [6,12].

3.3. Impact of short-term demand elasticity on social welfare

Figure 4 compares changes in social welfare for different cases of demand elasticity (D_e^{ela}) and risk aversion (β). As social welfare cannot be compared consistently assuming changes in the WTP function, the impact of risk aversion is shown as a difference to the social welfare of the risk-neutral case ($\Delta\mathbb{W}_\beta = \mathbb{W}_\beta - \mathbb{W}_{\beta=1.0}$).

Surprisingly, $\Delta\mathbb{W}$ reduces with increasing demand elasticity on the EOM and risk-averse agents. To understand this outcome, it is necessary to focus on the integrated WTP of the consumer (consumer's revenue), and the costs of the GenCos individually. Table 2 summarizes both perspectives showing differences between risk-averse and risk-neutral cases. For the GenCos, the differences in investments in peak technology become negative when participants are risk-averse and demand becomes elastic. Less capacity directly translates into less capacity-related costs (CAPEX) and also fewer costs for operation (OPEX).

However, on the energy market, a marginal increase in missing capacity is causing prices to spike more often. Hence price spikes impact the consumer's costs. Figure 5 gives an overview of scarcity prices for different amounts of elastic demand and risk aversion. We identify two underlying price-effects that are caused by demand elasticity. On the one hand, demand elasticity leads to the effect that exceptional scarcity prices reduce (arrow (1)). On the other hand, investment costs still need to be recovered. Therefore, prices and duration of times in which inframarginal rents are obtained will increase (arrow (2)). Both effects are more pronounced if participants are risk-averse ($\beta = 0.1$), i.e., there is a deficit of capacity. These effects on price spikes also become visible in the change of consumer's revenue (i.e., expected integrated WTP, $\mathbb{E}[R_{co}]$). Table 2 shows an increase in changes in consumer's revenue for higher volumes of elastic demand.

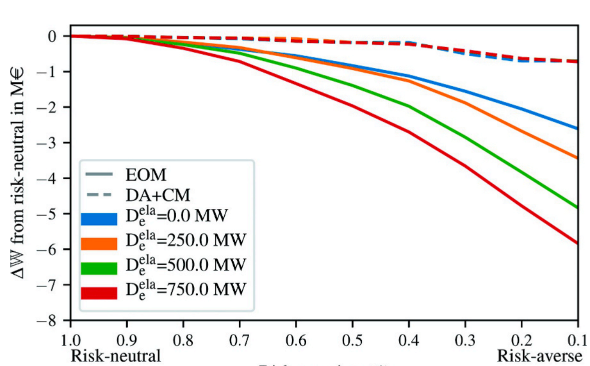

Fig. 4. Comparison of loss of social welfare for EOM and case with complementary capacity market. Depicted series are offset so that each risk-neutral optimum coincides with zero.

Finally, taking both sides into account, the difference in loss of consumer's revenue and GenCo's costs becomes larger with increasing demand elasticity resulting in a net loss of social welfare.

Contrasting the *EOM* case, for the ***DA+CM*** case, social welfare mainly varies with increasing risk aversion (cf. Fig. 4). Changes in social welfare with the demand elasticity are not significant given the capacity target is set perfectly. Due to the CM, the installed capacity remains constant, accounting for this effect as energy prices mostly remain unchanged. The remaining change in social welfare can be explained by risk-averse behavior, shifting capacity to less capital intense technologies with higher operating costs.

3.4. Impact of short-term demand elasticity on participants' surpluses

The impact of demand elasticity and risk aversion can also be observed on an agent level (Fig. 6). For illustrating the surpluses, welfare transfer from Consumer to GenCos is depicted over the considered demand elasticities for the risk-averse participants ($\beta = 0.1$). Resembling a perfect market, surpluses for GenCos are zero for the risk-neutral case, while surpluses are positive for risk-averse cases. With increasing risk-aversion $\Delta\mathbb{W}$ stays within the order of 1M€ (cf. Fig. 4), while the expected surplus of GenCos is in the order of 400M€ (cf. Fig. 6). As $\Delta\mathbb{W}$ remains small, a welfare transfer from consumer to GenCos occurs. This welfare transfer can be approximated by the sum of GenCo's expected surpluses for the risk-averse case minus expected surpluses for the risk-neutral case (which is zero). This approximation is meaningful as the change in total welfare is orders of magnitudes smaller than the welfare transfer. We generally observe surplus transfer induced by risk aversion benefiting the GenCos (all bars are positive). Risk aversion causes insufficient capacity leading to higher prices on both markets, and therefore, shifting the surpluses in favor of the GenCos. This effect is most prominent with the highest risk aversion.

In an **EOM** setting, increasing demand elasticity amplifies welfare transfer to GenCos (blue bars).

For a setting with the complementary **CM** agents' surpluses (orange bars) nearly stay unchanged following the constantly installed capacities. We observe that the surplus transfer is significantly reduced by implementing a CM. It shows that if the CM target is set correctly a CM can protect the consumer from losing surplus. For the considered demand elasticities the surplus transfer ranges from 320M€ to 290M€ reducing the surplus transfer range from 170M€ for the *EOM* case to 30M€ for the *DA+CM* case.

3.5. Impact of short-term demand elasticity on generation adequacy

We observe the effect of decreasing exceptional scarcity hours for increasing demand elasticity also in terms of Loss-Of-Load-Expectation (LOLE). Load is involuntarily curtailed if the electricity price reaches the price cap as a consequence of insufficient capacity. Figure 7 shows a plot of LOLE dependent on risk aversion and demand elasticity. As stated, hours of exceptional scarcity are directly linked to the installed capacity. Therefore, the trends are closely connected to the installed capacity. For the **EOM** we can identify two results:

Table 2
Summary of impact of risk aversion and elastic demand on installed capacities, consumer's revenue, GenCos costs, and social welfare. All values show the change induced by risk-aversion with respect to the risk-neutral case: $f(x) = x_{\beta=0.1} - x_{\beta=1.0}$.

			EOM				DA+CM			
	D_e^{ela}		0MW	250MW	500MW	750MW	0MW	250MW	500MW	750MW
Δ_{RA-RN}	Base	MW	− 239.64	− 241.79	− 242.84	− 244.4	− 239.64	− 241.79	− 242.84	− 244.4
	Peak	MW	31.05	18.66	− 7.89	− 25.89	239.64	241.79	242.84	244.4
	$\mathbb{E}[R_{co}]$	M€	− 9.55	− 11.15	− 13.95	− 16.13	− 0.0	− 0.05	− 0.09	− 0.14
	$\sum_{gc\in\mathcal{GC}}\mathbb{E}[CAPEX_{gc}]$[a]	M€	− 6.22	− 6.51	− 7.03	− 7.4	− 2.4	− 2.42	− 2.43	− 2.44
	$\sum_{gc\in\mathcal{GC}}\mathbb{E}[OPEX_{gc}]$[b]	M€	− 0.72	− 1.2	− 2.09	− 2.89	3.1	3.08	3.05	3.03
	$\sum_{gc\in\mathcal{GC}}\mathbb{E}[C_{gc}]$	M€	− 6.94	− 7.71	− 9.12	− 10.28	0.7	0.66	0.63	0.59
	$\mathbb{W}$	M€	− 2.61	− 3.44	− 4.84	− 5.84	− 0.7	− 0.71	− 0.72	− 0.72

[a] CAPEX relates to first line of Eq. (1k)
[b] OPEX relates to second line of Eq. (1k)

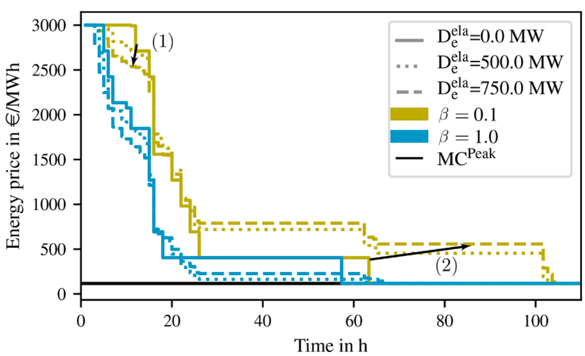

Fig. 5. Ordered expected energy prices on the EOM. (1) indicates a decrease of exceptional scarcity hours with more elastic demand, (2) an increase of other scarcity hours.

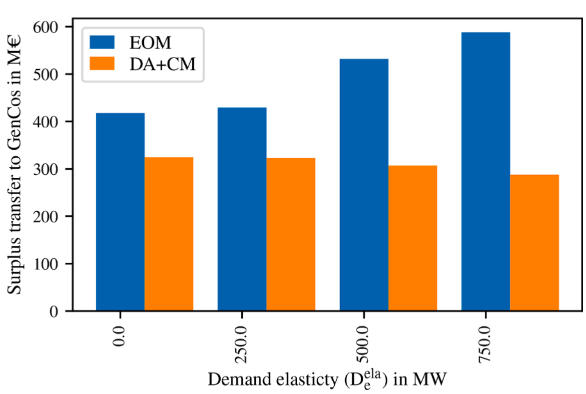

Fig. 6. Surplus transfers from the consumer to the GenCos due to risk aversion.

1. The higher the demand elasticity, the less the exceptional scarcity hours occur, and thus, the lower the LOLE.
2. Risk aversion leads to more scarcity hours as less total capacity is installed. While the optimization clears with 12.0h LOLE with risk-neutral participants, it nearly doubles in the case of risk-averse participants

Considering a complementary **CM**, the LOLE also decreases with rising demand elasticity. However, the total installed capacity is fixed through the CM. Thus, the LOLE shows no sensitivity to risk aversion and remains constant to changes of β. Extending the work of [5] by demand elasticity, Petitet et. al's conclusion remains valid: security of supply can be significantly increased using a CM with a well-defined capacity target.

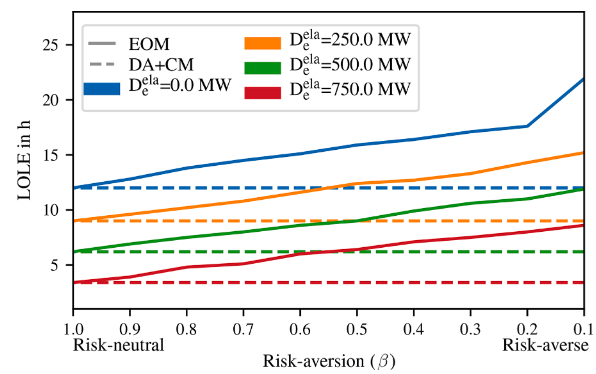

Fig. 7. Comparison of LOLE.

3.6. Impact of capacity demand

In reality, the social optimal capacity target is not known when set. Consequently, we assess the impact of a non-ideally set capacity target as shown in Fig. 8. Again, differences with respect to the system optimum ($\beta = 1.0$, ideal capacity target) are plotted.

Different effects are dominant in the case of risk-neutral and risk-averse participants. With risk-neutral participants (solid lines), setting the capacity target lower than optimal has no impact on social welfare. In that case, the capacity target is not binding and therefore capacity prices reduce to zero resembling an EOM as can be seen on the right side of Fig. 4. Thus, this setting can be used as a benchmark (cf. dotted gray lines). However, setting the target above the ideal demand has a

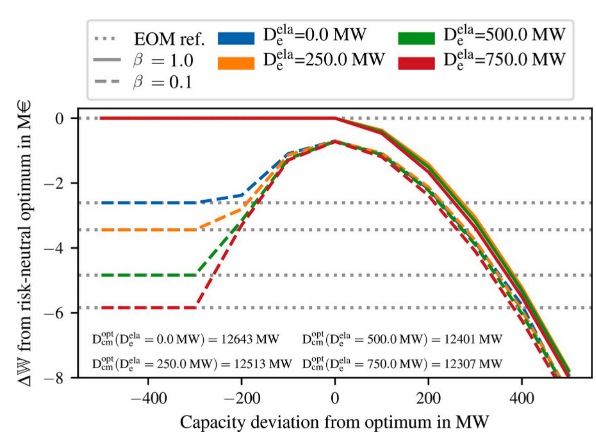

Fig. 8. Impact of non-ideally set capacity target on social welfare. Leftmost data points can be taken as EOM benchmark. For comparison the social optimal capacity targets are mentioned as D_{cm}^{opt}.

negative impact, as additional capacity introduces extra costs.

For the risk-averse case (dashed lines) the results show that the choice of the capacity target has a greater impact on social welfare. Particularly when the demand is short-term elastic social welfare differences are visible when setting the capacity target too low.

If the capacity target is not binding (left) it is set too low (for all cases at a deviation from the capacity optimum of − 300MW). It becomes clear that setting the capacity target below the ideal target will never result in a worse performance than the EOM setting as the capacity market will clear with a capacity price of 0€ /MW. For the inelastic case, the figure shows that the optimal capacity target can be missed by 200MW in both directions while the system still performs better than the EOM setting. This range increases for high demand elasticities. Additionally, the possible welfare gain for introducing a capacity market increases with high shares of demand elasticity. As for risk-neutral participants setting the capacity target above the optimal target introduces extra costs. Here, the worse performance in comparison with the EOM can be achieved when setting the target higher than 200MW to 300MW depending on the amount of elastic demand.

In summary, we find that implementing a capacity market can improve social welfare when the target is set within the mentioned bounds, especially if participants behave risk-averse and energy demand is short-term elastic.

4. Conclusion

The presented study provides a quantitative analysis of the performance of an energy-only market and an energy market complemented with a capacity market while considering risk-averse investors and short-term demand elasticity. This work elaborates whether implementing capacity markets still provide a better economic outcome and perform better in terms of generation adequacy if energy demand becomes short-term elastic.

To answer this question, we used an annualized capacity-expansion planning problem, resembling a non-cooperative game. The problem was solved using an Alternating-Direction-Multiplier-Method.

We confirm previous findings showing that implementing a capacity market protects against capacity shortages induced by risk aversion while shifting the generation mix towards technologies with low investment costs. The amount of short-term energy demand elasticity negatively correlates with the optimal peak capacity.

Our case study extends previous works and contributes to the literature by providing a formulation to represent capacity markets, short-term demand elasticity, and risk-averse behavior in a single model. It allows analyzing the performance of energy-only markets as well as markets complemented with a capacity market in economic terms and in terms of generation adequacy.

Given the modeling assumptions, we show that social welfare losses through risk aversion increase with increasing short-term demand elasticity for the energy-only-market. The centralized capacity market setting performs better than the energy-only market if the capacity target is set ideally. In addition, we identify the capability of capacity markets to dampen the welfare transfer between risk-averse agents.

In terms of security of supply, our stylized case study shows that a short-term elastic demand leads to lower numbers of loss-of-load-expectation. With an ideally set target, a capacity market outperforms an energy-only market while differences are more significant with low levels of demand elasticity.

Moreover, we conduct a sensitivity analysis of the capacity target showing that capacity markets can have a positive effect on social welfare if agents behave risk-averse even if the capacity target slightly deviates from the social optimal setting.

To address the targeted research questions only necessary features were considered in the presented model, also to keep the problem computationally tractable and to make sure targeted effects were not interfered with by other model constraints. These impose certain limitations on the applicability of this model to real-world problems. Therefore, future research could introduce features such as network constraints, ramping constraints, unit commitment decisions, reserve and balancing markets, and, e.g., cross-border participation of capacity on the capacity market. Additionally, future research would benefit from relaxing the assumption of homogeneous risk-perception. Considering long-term investments could shed light on possible pathways of the electricity system. Lastly, we showed that agents' attitudes towards risk lead to higher average prices and, thus, to an increase in profit. In theory, strategic agents could exhibit similar behavior to risk-averse agents by withholding capacity. Disentangling these effects would be of particular interest to regulators and an interesting contribution to future research.

CRediT authorship contribution statement

Steffen Kaminski: Conceptualization, Methodology, Software, Writing - original draft, Formal analysis, Visualization. **Hanspeter Höschle:** Conceptualization, Methodology, Writing - review & editing. **Erik Delarue:** Supervision, Writing - review & editing.

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.

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