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Last update: October 21, 2020

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Energy-only vs. capacity markets: impact of hedging opportunities considering risk-averse investors

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Abstract—In this study, an agent-based model is developed to examine the impact of long-term bilateral contracts on the performance of energy-only markets and markets with capacity remuneration mechanism (CRMs). Specific emphasis is put on hedging via bilateral forward contracts. We found that bilateral contracts can indeed incentivize investments in new capacities and help to reach a relatively safe system margin, but at an increase in total system costs. Implementing CRMs, in the presence of bilateral contracts, lead to a higher and more stable system margin while maintaining the total system cost on a similar level.

Keywords— Hedging opportunities, Capacity remuneration mechanism, Risk aversion, Agent-based modelling

NOMENCLATURE

A. Indexes

i	Scenario
j	Technology type
y	Year
d	Day
h	Hour

B. Symbols

$f_{j,y}$	Fixed cost components of technology type j in year y (€/MWh)
$G_{i,j,y}$	The total installed capacity of technology type j in year y under scenario i (MW)
$\overline{G}_{j,y}$	The upper bound of installed capacity of type j in year y (MW)
$\underline{G}_{j,y}$	The lower bound of installed capacity of type j in year y (MW)
$g_{i,j,y,d,h}$	The actual power output of technology type j in year y on representative day d at hour h (MW)
$inv_{i,j,y}$	The investment in technology type j in year y (MW)
$L_{i,y,d,h}$	The load in year y on representative day d at hour h (MWh)
$ll_{i,y,d,h}$	Load loss in year y on representative day d at hour h (MWh)
$v_{j,y,d,h}$	Variable cost components of technology type j in year y on representative day d at hour h (€/MWh)
$VoLL$	Value of lost load (€/MWh)

I. INTRODUCTION

The transition of the European electricity system requires intensive integration of intermittent renewable energy sources. These high volumes of renewable power in the electricity system, however, both reduce average electricity prices (i.e. the merit-order effect) and make price profiles more volatile. Therefore, it has been argued that an energy-only market (EOM) may fall short in attracting new capacity investments, and may jeopardize generation adequacy, especially during peak load periods. As a response, many member states have either implemented or are implementing capacity remuneration mechanisms (CRMs) to complement the energy markets. In such systems, investors depend on both (unstable) revenues from the electricity market and a (stable) revenue stream from the CRMs.

The capacity market (CM) has sparked a lively discussion in both academia and industry within the energy sector. On the one hand, CM is expected to ensure a secured supply. On the other hand, it might lead to distortions in the market and therefore to higher total system costs. Yet different in selecting key parameters, some European countries such as UK, France, Italy and Poland have already implemented their CMs, with some other countries following [1].

Recently, several studies have quantitatively analysed the performance of EOM designs and their combinations with CRMs while accounting for investors' risk-averse behaviour [3]–[6]. The main conclusions from these papers were that (i) uncertainty and risk-aversion significantly influence the performance of CRMs, and (ii) in the presence of uncertainty and risk-averse behaviour, a market design with a CRM provides more stable investment signals resulting in less need for load curtailment and higher welfare. Nevertheless, risk-hedging opportunities such as forward markets, long-term bilateral contracts (BCs) typically have not been included. In fact, the risk-aversion nature of generation companies results in a vast majority of energy traded via BCs instead of in the day-ahead market (DAM). For instance, in Germany, the largest and most liquid market in the EU by far, the energy traded via BCs accounts for more than 60% of the total volume [2].

The aforementioned studies followed either a microeconomic equilibrium modelling approach or a system dynamics approach. Besides the questionable underlying assumptions such as a stable market equilibrium and a fixed system structure, integrating a BC pricing mechanism in the context of long-term energy system transition can be challenging for these modelling approaches. Thus, an agent-based model is developed to analyse, in the presence of uncertainty and risk-averse investors, the influence of bilateral contracts (BCs) on the performance of a capacity market (CM). These research findings may contribute to a more efficient design of a CM by providing insights into the

mapping from market designs (e.g. target system capacity) to design objectives (e.g. total system cost and loss of load expectations (LOLE)).

To the best of our knowledge, the method developed in this study is the first one that allows an appropriate synthesizing of DAM, CM and BC market in a long-term electricity market model. More specifically, we developed an agent-based model to analyse the implications of BC on the performance of a CM in the presence of risk-averse agents. The model accounts for investment decision making by including (i) risk-averse behaviour of generation companies, (ii) capacity market and (iii) bilateral contract pricing model. Furthermore, the model also accounts for the interaction among agents by incorporating supply and demand mechanism as well as for the diversity among agents. In particular, the model is used to shed light on the following research question:

Given risk-averse investors, what is the influence of bilateral contracts on the evaluation of the energy-only market vs. capacity market?

The findings suggest that, without implementing a capacity market, bilateral contracts can incentivize investments in new capacities and help to reach a relatively safe system margin, at an increase in total system costs (compared to the energy-only market). Implementing CRMs, in the presence of bilateral contracts, leads to a higher and more stable system margin while maintaining the total system cost on a similar level.

The paper is organized as follows: Section II describes the concepts underpinning the model structure and provides an explanation of the agent-based model developed in this study. The results are presented and discussed in section III. Finally, conclusions are drawn in section IV.

II. THEORY AND METHODS

This section describes the concepts and modelling considerations required for the representation of a stylized power system that consists of a day-ahead market (DAM), CM and BC forward market. The description follows the standard ODD (Overview, Design concepts and Details) protocol developed by Grimm *et al.* [3].

A. Overview

1) Purpose, entities, and state variables

Three types of agents are considered in our model, namely generation companies, the market operator, and consumers. Generation companies are characterized by the state variables technology portfolio and corresponding risk-exposure level. The market operator is characterized by DAM price and CM price. Consumer agents take demand and value of lost load (VoLL) as their state variables.

2) Process overview and scheduling

Five main processes are executed in our generic agent-based model: BC pricing, determination of the DAM prices, determination of CM price, decommissioning of power plants and investment in new capacity.

Fig. 1. Flow chart diagram of the agent-based model.

As shown in Fig. 1, the narrative of the agent-based model is as follows. At the beginning of each milestone year, agents first decommission generation units that have reached their lifetimes, followed by an investment decision making process wherein agents make investment decisions sequentially. The investment process is further divided into investment rounds. During each round, each agent is allowed to invest only once and in one generation unit. To mitigate the influence of first-mover advantage, the size of a generation unit is fixed and set in a manner that all agents have approximately equal chances of being the first investor in the whole investment process. The investment process is terminated when none of the agents has invested in the last round, i.e. no agent is still willing to invest anymore. It is assumed that preceding agents' investment decisions are known by the subsequent agents.

With the up-to-date capacity mix, day-ahead market simulation is executed daily and in two steps: bidding and market clearing. The bidding process in the spot market is carried out by the energy producers and all generators are assumed to bid their marginal costs. Then, the market operator determines the market price by maximizing social welfare. Based on the market prices and committed productions, the avoidable cost¹ of each power plant is calculated and bid accordingly in the CM, where the bids are sorted in a price ascending order to determine the CM price in the present milestone year (see the capacity market clearing model in *Submodels* section for more details). Finally, BC pricing is performed based on the up-to-date capacity mix to determine, for each type of technology and each future period, the contracting quantity and price. This arrangement regarding BC pricing thereby implicitly assumes that the price-quantity

¹ The avoidable cost is the expense that can be eliminated by not doing the underlying activity. In the context of this study, for new power plants, the fixed costs, variable costs and capital costs can be avoided if the agents decide not to invest in any power plants; for existing power plants, the capital

costs are not avoidable because the already performed investment is irreversible.

pair of BCs are updated every milestone year according to the new system capacity mix.

B. Design concepts

- **Basic principle:** the principle applied in the model is the expected utility theory. This theory is used to describe the decision making on investment of capacity.
- **Emergence:** emergent phenomena include the evolution of the capacity mix, DAM prices and CM prices.
- **Adaptation/Prediction:** generation companies adapt their investment strategies based on three key information: future DAM price projections, future CM price projections, and BC terms (i.e. prices and quantities). The generation of this information is elaborated later in *Submodels* section.
- **Objective:** the objective of the generation companies is to optimize their investment portfolio to maximize profit according to their risk aversion levels.
- **Learning:** none of the agents in the model are endowed with learning methods.
- **Sensing:** agents are assumed to know without uncertainty the preceding generation companies' investment decisions. Nevertheless, the agents are facing uncertainties regarding future load growth and therefore prices in DAM, CM and BCs.
- **Interaction:** generation companies interact with each other indirectly through the price signals in the DAM, CM. Further, these generation companies interact with consumer agents directly through the conclusion of BCs. That is, a new investment placed in the market will lead to an increase in system installed capacity and consequently a drop in the market price. The market price change will further alter the CM prices and the consensus being reached in BCs. This change in various markets will be sensed by other agents who adapt their investment decisions accordingly.
- **Stochasticity:** future load growth is a stochastic process characterized by the geometric Brownian motion (GBM) model. Hence, the future DAM prices, productions and CM prices, which are retrieved and/or derived based on a stochastic generation expansion planning model, are also stochastic. The order of how energy producers carry out the bidding process and the investment is random.
- **Observation:** the observation consists of system capacity mix, resulting system margin and total system costs.

C. Details

1) Initialization

Without loss of generality, the model is initialized with a uniformly distributed existing capacity mix in the system, i.e. different types of technologies have the same market shares and their construction time points are uniformly distributed in the historical periods. It is worth noting that it is intended to deviate the initialization from the long-run equilibrium solution to ensure that reaching long-run equilibrium is not a result of the initial capacity mix. Moreover, all agents are fully rational, i.e. without technological preferences and a priori beliefs. Finally, agents are not subject to budget constraints.

2) Input data

In this study, the Belgian electric power system load of the year 2015 is used with a VoLL value of 2000€/MWh². A highly stylized setting is assumed. The key technological parameters are shown in Table 1.

Table 1. Technological parameters.

Technology	Variable cost [€/MWh]	Fixed cost [€/kW/a]	Capital cost [€/kW]	Size of one unit [MW]
Base-load	12.5	80	3000	100
Peak-load	45.7	25	800	100

3) Submodels

a) Future load growth scenario generation model

In this study, we assume that the future load growth is governed by Geometric Brownian Motion (GBM), where the proportional change in load L during each time step t is assumed to have a constant instantaneous drift μ and volatility σ . GBM has been widely used to create stochastic processes (e.g. [4], [5]). Mathematically, the GBM formulation is given by Eq. (1).

$$dL = \mu L dt + \sigma L dW_t \quad (1)$$

where L and dL denotes respectively the load and load growth at time t ; W_t represent a Wiener process³.

b) Modelling of risk-aversion

We assume that all agents are risk-averse and show a varying degree of risk aversion. Several measures of risks are commonly used in the energy sector, namely variance, semi-variance, Value at Risk (VaR) and Conditional Value at Risk (CVaR). A brief explanation and comparison of these measures can be found in [6]. In this study, risk-aversion of agents are measured with CVaR as it does not require a profit target value [7] and it is a coherent measure of risk as defined in [8].

The fundamentals of CVaR are illustrated in Fig. 2, where α is a pre-defined shortfall probability to derive a VaR breakpoint which will be used to calculate CVaR. Then, the risk-adjusted NPV can be calculated by Eq. (2).

$$NPV_{risk-adjusted} = E[NPV] - \beta \cdot risk_{preimum} \quad (2)$$

where $\beta \in [0,1]$ determines the risk-averse level of the agent; $E[NPV]$ is the expected value of NPV distribution and $risk_{preimum}$ is the gap between CVaR and $E[NPV]$, i.e. $risk_{preimum} = E[NPV] - CVaR$. Thus, the risk-adjusted NPV can be rewritten as Eq. (3):

$$NPV_{risk-adjusted} = E[NPV] \cdot (1 - \beta) + CVaR \cdot \beta \quad (3)$$

² This relatively low value is chosen to reflect some degree of demand flexibility as explained and used in [9].

³ In a discrete time series, the changes between two time steps follow a zero-mean normal distribution with variance equals the length of the time

step. In the context of load projections, this means the random jump distance between two time steps are proportional to the length between two milestone years.

Fig. 2. Illustration of the modelling of risk-aversion [6]

The simulation results shown later in this study are based on an α value of 0.1 (i.e. 90% confidence level) and a β value of 0.75 (which is the same as in [6], where a sensitivity analysis of the risk-aversion parameters in the context of the capacity market can be found).

c) The stochastic generation expansion planning model

The stochastic generation expansion planning model (SGEP) provides future market condition projections for the DAM prices and capacity mix evolution. Projections for the CM price and BC price-quantity pair requires further processing over these primary outcomes (see capacity market clearing model and bilateral contract negotiation model further on).

This SGEP model takes the technological cost and the load growth scenario as exogenous input and minimizes the weighted average costs among all scenarios. The SGEP model is subject to constraints such as energy balance constraint (Eq.(5)), generation limits (Eq.(6)), capacity mix evolution constraints (Eq.(7)) and installed capacity constraints (Eq.(8)). Considering that this SGEP will be dispatched for a large number of times, it is formulated in a linear way to reduce the computational complexity. The mathematical formulation is as follows:

- Objective function:

$$\text{Min } \sum_{i=1}^N (\sum_{j=1}^J \sum_{y=1}^Y G_{i,j,y} \cdot f_{j,y} + \sum_{d=1}^D \sum_{h=1}^H g_{i,j,y,d,h} \cdot v_{j,y,d,h} + \text{VoLL} \cdot ll_{i,y,d,h}) \quad (4)$$

- Constraints:

$$\sum_{j=1}^J g_{i,j,y,d,h} \cdot \Delta t + ll_{i,y,d,h} = L_{i,y,d,h} \quad (5)$$

$$0 \leq g_{i,j,y,d,h} \leq G_{i,j,y} \quad (6)$$

$$G_{i,j,y} = \sum_{t=0}^{n_j-1} inv_{i,j,y-t} \quad (7)$$

$$\underline{G}_{j,y} \leq G_{i,j,y} \leq \overline{G}_{j,y} \quad (8)$$

d) The capacity market clearing model

The formulation of the CM clearing model is illustrated in Fig. 3. This CM clearing is performed on an annual basis with a pre-determined target capacity to ensure supply adequacy during peak load hours. As for the supply curve, they are sorted in a price ascending order and matched with the target capacity to reach a CM price. Although the CM is uniformly priced, the offers have to differentiate among existing and new power plants because of their different avoidable cost. Specifically, the avoidable cost for existing power plant consists of fixed and variable costs, while new power plants additionally consider capital costs. In this study, a marginal cost-based approach, which has been adopted in

[6], [9], [10], is used to calculate the bid price. That is, the power plants bid the gap between their avoidable costs and revenues in the DAM if the avoidable costs are uncovered, and zero otherwise. Mathematically, the bids of existing and new power plants in the CM are shown in Eq. (9). Note that the capacity market clearing model, when taking future DAM prices and productions into account, is used in the same manner to project CM prices in the future. In this study, we use a target system margin of 15% (i.e. the target capacity is 115% of the peak load).

$$\text{CapacityBid}_{i,j,y} = \max(\text{AvoidableCost}_{i,j,y} - \text{DAMRevenue}_{i,j,y}, 0) \quad (9)$$

Fig. 3. Capacity market clearing model [6]

e) The bilateral contract pricing model

Being different from the above submodels where only generation companies are active in decision making, the BC pricing model also involves consumers as a counterparty. To begin with, both parties should have themselves prepared by determining two key price-quantity pairs: the initial proposal and a bottom-line proposal. During the negotiation process, both parties start with their initial proposal and strive to reach an agreement, however, if the ongoing negotiation breaks through the bottom line proposals of any party, the negotiation process will be terminated without an agreement and therefore no BC is concluded.

For consumers, contracting more leads to less exposure to market risks and thus a higher premium, i.e. the concluded contracting prices will increase as the contracted amount increases. For the sake of simplicity, we describe prices and quantities with a linear relationship between 100% and 0%. On the one hand, contracting 100% is risk-free and therefore the price of each type of technology is, among all future load growth scenarios, the highest electricity prices. On the other hand, contracting 0% means the consumer is fully exposed to market price risks and the equivalent “contracting” price is determined by the average electricity price in the market. Note that these settings implicitly considers the correlation between consumers’ consumption profiles and generators’ dispatch profiles. With these two boundary conditions in disposal, we can determine, for each contracting quantity, the corresponding BC prices. In this study, the contracting percentage is exogenously fixed at 60%, which is a commonly observed value in a number of EU member states [11].

III. RESULTS AND DISCUSSION

In this section, we describe and discuss the influence of the BC on the performance of the CM. We use an EOM simulation as a reference case. Experimental cases are created by adding different market designs to the reference case. The key performance indicators are capacity mixes and total system levelized cost.

Simulations are repeated five times with different random seeds. The resulting capacity mixes with different market settings and their corresponding total system levelized costs are shown in Fig. 4. The error bars represent the standard deviation of the repeated simulation results.

Fig.4. Simulation results of the capacity mix under different market settings. Where DAM refers to the day-ahead market, CM stands for the capacity market and BC stands for the bilateral contract. “Base” and “Peak”, coloured respectively in blue and orange, represent the share of base- and peak-load technologies.

With DAM only (i.e. EOM), the investments of the agents stably halt at 99.5% of annual load peak because of the necessity of scarcity rent to recover the fixed cost. Accounting for BC on top of DAM realized a higher system margin thanks to the risk premium paid by the consumers. This over-capacity mainly attributes to peak-load technology, implying that peak-load technology benefits more from bilateral contracting. This is because peak-load technology has a higher risk in terms of capital cost recovery and therefore a wider range of NPVs. Bilateral contracting makes peak-load technology more favourable by squeezing its NPV distribution. Because of the strong bias towards peak-load technology, the total system levelized cost is similar to the cases with CMs implemented (i.e. cases “DAM+CM” and “DAM+CM+BC”), which accomplish systematically higher installed capacities.

Although adding CM to DAM renders an average system margin of 26%, the relatively high variation ($\pm 4\%$) implies that the implementation of CM is less-than-ideal in guaranteeing a reliable system margin. Moreover, the implementation of CM mainly contributes to the investment in peak-load technology because the revenues from the capacity market contribute largely to its fixed cost recovery, which substantially reduces the risk of adopting a peak-load technology. This insight is in line with the findings in [10].

By further adding BC to CM and DAM, the realized system margin systematically can be spurred to 28.1% with a reduced variation level, implying that bilateral contracting can, on top of increase system margin, help to reduce the uncertainty of capacity mixes. Further increase in the share of peak-load technology has also been observed due to a more stable revenue in DAM and BC, besides the stable revenue

from CM. In this case, the highest system margin undoubtedly results in the highest total levelized system costs.

The results suggest that the system margin realized by accounting for BC is built upon a significant reduction in system efficiency, mainly because of the strong bias towards peak-load technologies. Implementing a CM on top of the DAM can realize a higher system margin, without increasing the total levelized system cost (compared to having BC and DAM). Nevertheless, the system margin attainment achieved by implementing CM is subject to a relatively high level of uncertainties stemming from the uncertain load growth paths. These uncertainties can further be damped by implementing DAM, CM and BC at the same time.

This approach, however, has some limitations. First, technology types are highly stylised to perform a concise analysis. Nevertheless, the model can easily be extended to include more technology types for real-world applications. Second, the information on which adaptation/prediction is based (i.e. price projections) assumes a perfectly competitive market in the future and neglects unit commitment constraints, which can potentially distort the market prices. Third, the model assumes a linear relationship between contracted price and quantity. Although the relationship, in reality, is often non-linear, the positive correlation generally holds. These limitations, along with the discrete nature of representative days, might result in less precise price signals regarding investment decision making but also open opportunities for future researches.

IV. CONCLUSIONS AND OUTLOOK

This study was conducted to answer the following research question: *Given risk-averse investors, what is the influence of bilateral contracts on the evaluation of the energy-only market vs. capacity market?*. To answer this question, we developed an agent-based model with risk-averse agents. The model consists of three major market modules: day-ahead market, capacity market, and bilateral contracts.

We found that, given the simulations and parameters that were used, the existence of bilateral contracts can lead to a system margin of 15.7% and at an increase of system cost. Without significantly increasing the total system levelized cost, a system margin of 26% can be achieved by implementing a capacity market on top of the day-ahead market. If all three markets are in place, the highest system margin can be reached, together with the lowest uncertainty concerning the capacity mix.

From a methodological viewpoint, the present agent-based model allows for appropriate integration of various major market components in a long-term electricity market model, thereby establishing a modelling framework capable of capturing the interaction among these market components and their synergistic effects.

Future work will focus on accounting for a bilateral contract negotiation mechanism. Demand-side counterparties will be modelled as consumer agents with heterogeneous load profiles and preferences.

ACKNOWLEDGMENT

This work is supported by the Research Foundation – Flanders (FWO) under the SBO project ELDEST (Energy PoLicy DEcision Support Toolbox) with project number S006718N.

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On the research group:

The **Energy Systems Integration & Modeling Group** is part of the division of Applied Mechanics and Energy Conversion (TME) of the Department of Mechanical Engineering of KU Leuven in Belgium. E. Delarue and W. D'haeseleer lead this research group, currently about 15 PhD students and post-doctoral research fellows, dedicated to the modeling of integrated energy systems and markets. This young research group has already gained significant expertise and international recognition in the field. A major strength of this group is its interdisciplinary focus (techno-economic models, link to energy policies and markets). The group is further strongly embedded in EnergyVille, an association of the Flemish research institutes KU Leuven, VITO, imec and UHasselt in the field of sustainable energy and intelligent energy systems. EnergyVille brings research, development, training and industrial innovation together under one name, in close cooperation with local, regional and international partners.