2022 18th International Conference on the European Energy Market (EEM) | 978-1-6654-0896-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/EEM54602.2022.9921162

Societal Effects of Large-Scale Energy Storage in the Current and Future Day-Ahead Market: A Belgian Case Study

Emilia Rocha Ojeda‡, Lina Silva-Rodriguez*†‡, Anibal Sanjab*†, Madeleine Gibescu‡, and Elena Fumagalli‡.
* Flemish Institute for Technological Research (VITO), Boeretang 200, 2400 Mol, Belgium
{lina.silvarodriguez, anibal.sanjab}@vito.be
† EnergyVille, Thor Park 8310-8320, 3600 Genk, Belgium
‡ Copernicus Institute of Sustainable Development
Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, Netherlands
{e.rochaojeda, l.m.silvarodriguez, m.gibescu, e.m.fumagalli}@uu.nl

***Abstract*—As part of the energy sector transformation, a substantial deployment of large-scale energy storage systems (ESS) is expected to support the integration of variable renewable energy sources (VRES). Understanding the value of this technology is of high relevance for investors and policy markets to assess their potential role in future energy systems. The present paper develops a model aiming to assess how large-scale ESSs participating in the day-ahead electricity market affect the market social economic welfare (SEW). This model considers two alternative bidding strategies by the ESSs owners participating in the market (i.e., a price-taker and a price-maker approach). The presented analysis considers a large case study representing the Belgian wholesale day-ahead electricity market, in which, in addition to existing ESSs, additional storage capacity is simulated for varying shares of VRES. Results suggest there is an added societal value driven by the participation of large-scale ESS in the electricity market in Belgium.**

***Index Terms*—energy storage systems, energy arbitrage, social-economic welfare, strategic bidding, day-ahead electricity markets.**

I. Introduction

As variable renewable energy sources (VRES) are increasingly deployed in European power systems, large-scale energy storage systems (ESSs) are emerging as key technologies to support their efficient integration [1]. ESSs' ability to readily absorb, store, and re-inject electricity into the network enables them to provide critical services, such as peak shaving and energy shifting, thus reducing VRES curtailment and the start-up of costly peak generators [2]. These applications, however, require ESSs to purchase electricity at a low (off-peak) price and sell it at a higher (on-peak) price – a strategy known as energy arbitrage.

Extensive research has been carried out to investigate the value of ESSs for energy arbitrage applications from the owner's perspective [3], [4]. In contrast, fewer studies focus on quantifying ESSs' value from a societal perspective, and there is no clear consensus on whether the deployment of storage would have a negative (as discussed in [5]) or a favourable (as discussed in [4]) societal effect.

The present paper develops a rigorous model aiming to assess how merchant-owned large-scale ESSs affect social economic welfare (SEW) in day-ahead (DA) electricity markets while considering strategic bidding by the ESSs owners. The focus is on a price-maker approach in which ESS owners bid strategically and can affect the market-clearing price (MCP). In this setting, their optimal bidding strategies are derived based on a bi-level optimization approach. The strategic interaction between multiple ESS players is captured using a developed *best response approach* for each player, while considering bounded rationality measures (namely, using a k-1 level decision-making process) [6], [7]. In addition to the price-maker strategy, we also model a price-taker approach, in which the ESS owners' optimal bids are derived considering no induced impact on the MCP. Hence, a comparison of the results obtained in the two cases is also provided.

The proposed models are applied to a large case study representing the current and future Belgian power system. The societal effects of ESSs' participation in the Belgian day-ahead market are quantified by capturing changes in SEW and exploring the dependence of such changes on the generation mix, installed storage capacity, weather conditions, and bidding strategies of the ESS owners. The generated results showcase the possible transfer of surplus from producers to consumers and added societal value driven by the participation of large-scale ESS in the DA electricity market in Belgium.

II. Methodology

To achieve the aforementioned aim, two different problems are considered. First, the perspective of the market operator, which clears the market and derives the dispatch quantities and MCP, is taken into account. Second, the bidding strategies of large-scale ESSs players are investigated to generate the bids for participating in the DA market.

This work was partly supported by the energy transition funds project 'EPOC 2030-2050' organised by the Belgian FPS economy, S.M.E.s, Self-employed and Energy.

978-1-6654-0896-7/22/$31.00 ©2022 IEEE

A. Market clearing problem

The market clearing problem is seen from the perspective of the market operator, which aims at maximizing the SEW of the market. This problem is formulated in its simple form as follows:

$$\max_{\boldsymbol{q^D},\boldsymbol{q^G},\boldsymbol{q^S_{dis}},\boldsymbol{q^S_{ch}}} \sum_{t\in\mathcal{T}} \Big[\sum_{d\in\mathcal{D}} q^D_{d,t} p^D_{d,t} + \sum_{s\in\mathcal{S}} (q^S_{ch_{s,t}} p^S_{ch_{s,t}} - q^S_{dis_{s,t}} p^S_{dis_{s,t}}) - \sum_{g\in\mathcal{G}} q^G_{g,t} p^G_{g,t} \Big], \tag{1}$$

subject to:

$$\sum_{d\in D} q^D_{d,t} + \sum_{s\in S} (q^S_{ch_{s,t}} - q^S_{dis_{s,t}}) - \sum_{g\in G} q^G_{g,t} = 0\,;\lambda_t, \tag{2}$$

$$q^D_{d,t} \leq m^D_{d,t}\ \forall d \in \mathcal{D}, \tag{3}$$

$$q^G_{g,t} \leq m^G_{g,t}\ \forall g \in \mathcal{G}, \tag{4}$$

$$q^S_{dis_{s,t}} \leq m^S_{dis_{s,t}}\ \forall s \in \mathcal{S}, \tag{5}$$

$$q^S_{ch_{s,t}} \leq m^S_{ch_{s,t}}\ \forall s \in \mathcal{S}, \tag{6}$$

$$q^D_{d,t}, q^G_{g,t}, q^S_{dis_{s,t}}, q^S_{ch_{s,t}} \geq 0\ \forall d \in \mathcal{D}, \forall g \in \mathcal{G}, \forall s \in \mathcal{S}. \tag{7}$$

where $q^D_{d,t}$, $q^G_{g,t}$, $q^S_{ch_{s,t}}$ and $q^S_{dis_{s,t}}$ are the decision variables corresponding to the demand, dispatched generation, and ESS's charging and discharging quantities for each time unit t lying in the sets $\mathcal{D}$, $\mathcal{G}$, and $\mathcal{S}$, respectively. To participate in the market, players submit price-quantity bids $(p^D_{d,t}, m^D_{d,t})$, $(p^G_{g,t}, m^G_{g,t})$, $(p^S_{ch_{s,t}}, m^S_{ch_{s,t}})$ and $(p^S_{dis_{s,t}}, m^S_{dis_{s,t}})$, expressing their willingness to withdraw or inject electricity from/into the system. Constraint (2) guarantees the energy balance in the system, while (3)–(6) correspond to the maximum demand, generation, discharging, and charging bid boundary constraints. Lastly, (7) represents the non-negativity constraints of the decision variables. In this problem, the MCP is derived from the dual variable in the balance constraint (2), as in [8], corresponding to λ_t.

B. Bidding strategy of energy storage systems

When engaging in energy arbitrage, the operation and bidding strategy of ESSs depend on the electricity market prices. In this application, ESSs purchase electricity and charge when the price is low and sell and discharge when the price is high. This price is an outcome of the market-clearing process, which is determined based on the bids submitted by participants. Therefore, for the creation of their bids, ESSs players need to implicitly estimate the market price to maximize the profit achieved from the operation of their assets. To model the decision-making process of an ESS player, a two-step process is proposed. First, all the ESSs are assumed to look at historical MCPs, i.e., to derive a bidding strategy as price-takers. The results of the price-taker approach are used within a price-maker model in which the ESS player is considered to act strategically. The price-taker and price-maker approaches are explained next.

1) ESSs as price-takers: In the price-taker approach, ESSs assume to have no impact on the determination of the MCP, due to, for example, possessing minor market shares. Therefore, historical MCPs, together with the ESS's technical parameters, are used as an input to the ESS operation optimization model, i.e., to determine the optimal storage scheduling and obtain the charging and discharging quantities. The ESS operation optimization model aims at maximizing the ESS's operating profits throughout the considered day. These profits are calculated as the difference between the revenues and the costs from selling and buying electricity[1] as represented in the following formulation:

$$\max_{\boldsymbol{E_s},\boldsymbol{b_s},\boldsymbol{m^S_{ch_s}},\boldsymbol{m^S_{dis_s}},\boldsymbol{p^S_{ch_s}},\boldsymbol{p^S_{dis_s}}} \sum_{t\in\mathcal{T}} \lambda^h_t (m^S_{dis_{s,t}} - m^S_{ch_{s,t}})\Delta t, \tag{8}$$

subject to:

$$E_{s,t+1} = E_{s,t} + (\eta_{ch_s} m^S_{ch_{s,t}} - m^S_{dis_{s,t}}/\eta_{dis_s})\Delta t,\ \forall t, \tag{9}$$

$$R_{e_s}(1 - D_{oD_s}) \leq E_{s,t} \leq R_{e_s},\ \forall t, \tag{10}$$

$$E_{s,1} = R_{e_s} S_{oC_{s,0}},\ \forall t, \tag{11}$$

$$0 \leq m^S_{dis_{s,t}} \leq b_{s,t} R_{p_s},\ \forall t, \tag{12}$$

$$0 \leq m^S_{ch_{s,t}} \leq (1 - b_{s,t}) R_{p_s},\ \forall t. \tag{13}$$

$$p^S_{dis_{s,t}} = 0 b_{s,t}\ \forall t. \tag{14}$$

$$p^S_{ch_{s,t}} = 3000(1 - b_{s,t})\ \forall t. \tag{15}$$

where λ^h_t is the historical DA MCP, and $m^S_{dis_{s,t}}$, $m^S_{ch_{s,t}}$, and $E_{s,t}$, are the decision variables corresponding to the discharged power, charged power, and energy stored in the ESS during the time step Δt, which in most European markets corresponds to one hour. Decision variables $p^S_{dis_{s,t}}$ and $p^S_{ch_{s,t}}$ correspond to the bid prices for the discharging and charging operation. Moreover, the decision variable $b_{s,t}$ is a binary variable representing the charging ($b_{s,t} = 0$) or discharging ($b_{s,t} = 1$) status of the ESS. Regarding the constraints, (9) captures the intertemporal energy storage level of each ESS, where η_{dis_s} and η_{ch_s} are the discharging and charging efficiencies. Constraint (10) limits $E_{s,t}$ to the system rated energy storage (R_{es}) in the upper bound and to the energy level at the recommended depth of discharge (D_{oD_s}) in the lower bound, while (11) sets the initial $E_{s,t}$ equal to the initial state of charge ($S_{oC_{s,0}}$). Moreover, (12) and (13), limit the charging and discharging power to be lower or equal to the system's rated power (R_{ps}). Note that the binary variable $b_{s,t}$ restricts the storage operation to avoid simultaneous charging and discharging[2]. Lastly, since each ESS player must fulfil its charging and discharging bids in the whole time horizon, the bid prices for each player are set

[1]Note that additional operational costs, besides the charging costs, are not included in the analysis for simplification purposes.

[2]This optimization model can be applied to most energy storage technologies. In the case of batteries, battery degradation also plays a role in the operation of the ESS. However, due to the short modelling periods considered in this work, battery degradation is not included in the optimization problem.

to 0€/MWh for discharging bids, as formulated in (14), and 3000€/MWh for charging bids, as in (15). In this manner, it is guaranteed that the storage bid quantities are always accepted[3].

2) ESSs as price-maker: In the price-maker approach, it is assumed that the ESS players act strategically, aiming to influence the MCP by changing the bid quantities. The bids of strategic players in the electricity markets can be optimized based on a Stackelberg game structure. Stackelberg games are hierarchical games involving a leader who acts first and a follower who acts second. In these, the leader's objective function is affected by the follower's reaction to its actions. Therefore, the leader benefits by anticipating the follower's optimal reaction when optimizing its strategy [10]–[13]. In this case, as shown in Fig. 1, the strategic player (i.e., ESS) is the leader, deciding on its charge or discharge quantities ($m^S_{dis_{s,t}}$, $m^S_{ch_{s,t}}$) and prices ($p^S_{dis_{s,t}}$, $p^S_{ch_{s,t}}$) based on the objective of maximizing its profit, which is a function of the anticipated MCP (λ_t). The market operator would then be the follower, clearing the market for all the submitted bids, including the ones from the strategic player, to obtain the dispatch quantities ($q^S_{dis_{s,t}}$, $q^S_{ch_{s,t}}$) and MCP (λ_t).

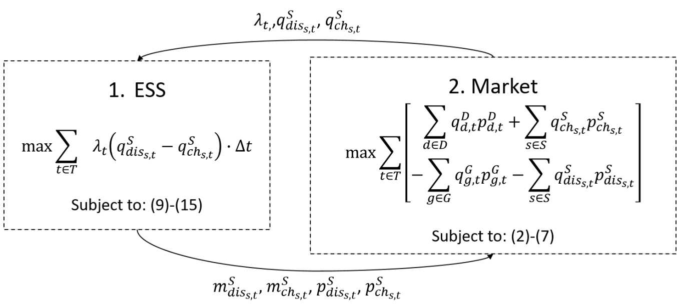

Fig. 1. Stackelberg game

Stackelberg games are traditionally formulated as bilevel optimization problems, where the follower's problem (i.e., lower-level problem) is added as a constraint to the leader's problem (i.e., upper-level problem). The upper-level problem, which maximizes the ESS's profits is presented in (16)-(18). Moreover, the lower level problem which anticipates the market clearing problem and maximizes the SEW, is represented in (19).

$$\max_{\boldsymbol{E_s}, \boldsymbol{b_s}, \boldsymbol{m^S_{ch_s}}, \boldsymbol{m^S_{dis_s}}, \boldsymbol{p^S_{ch_s}}, \boldsymbol{p^S_{dis_s}}} \sum_{t\in\mathcal{T}} \lambda_t (q^S_{dis_{s,t}} - q^S_{ch_{s,t}})\Delta t, \quad (16)$$

subject to:

$$E_{s,t+1} = E_{s,t} + (\eta_{ch_s} q^S_{ch_{s,t}} - q^S_{dis_{s,t}}/\eta_{dis_s})\Delta t \ \forall t, \quad (17)$$

$$(10) - (15), \quad (18)$$

[3]In recent market designs, this guarantee can be obtained through mutually inclusive linked-bids, also known as loop blocks (as, e.g., in [9]).

$$\begin{cases} \max_{\boldsymbol{q^D}, \boldsymbol{q^G}, \boldsymbol{q^S_{dis}}, \boldsymbol{q^S_{ch}}} \sum_{t\in\mathcal{T}} \Big[\sum_{d\in\mathcal{D}} q^D_{d,t} p^D_{d,t} + \\ \sum_{s\in\mathcal{S}} (q^S_{ch_{s,t}} p^S_{ch_{s,t}} - q^S_{dis_{s,t}} p^S_{dis_{s,t}}) - \quad \sum_{g\in\mathcal{G}} q^G_{g,t} p^G_{g,t} \Big], \\ \quad \text{subject to:} \qquad (2) - (7). \end{cases} \quad (19)$$

Note that $m^S_{dis_{s,t}}$, $m^S_{ch_{s,t}}$, $p^S_{dis_{s,t}}$, and $p^S_{ch_{s,t}}$ are decision variables in the upper level problem and parameters for the lower level problem. On the other hand, $q^S_{dis_{s,t}}$, $q^S_{ch_{s,t}}$ and λ_t are decision variables for the lower level problem and parameters for the upper level problem.

Note that the anticipated market clearing problem (19) is solved considering the bids from all the market players. To accomplish this, the strategic player is assumed to have access to the information required to estimate the bids from the producers and demand players (e.g., access to historical bids). As accessing this information can be challenging in practice, we consider the game-theoretic concept of level-1 thinking [6], in which – based on the absence of the needed information – each player reverts to optimizing its strategy based on the assumption that other players are not strategic [14][4]. In this sense, the strategic player optimizes its bidding strategy considering that the other ESS players behave as price-takers. The charge and discharge bids of the other ESS players are then derived from the price-taker model in (8)-(15) and are assigned as inputs for the anticipated market clearing model. Once the price-maker problem is solved for all the ESS players, the charging and discharging bids are obtained[5]. This information, together with the demand and generation bids, is used, as input, to solve the market clearing problem described in (1) - (7). As a result, the dispatch quantities and MCP are obtained. This process is illustrated in Fig. 2.

III. Case Study

The case study models the Belgian DA wholesale electricity market in which the existing pumped hydroelectricity storage (PHES) capacity is considered, in addition to large-scale battery energy storage systems (BESS) of different sizes for varying VRES shares. Twenty-four-hour periods are modelled for four representative days of the year, selected in such a way to consider seasonal changes in demand and VRES generation. Fig. 3 in the Appendix shows the demand and VRES capacity factors values for the selected dates. The January date has the highest demand and lowest solar availability, while the June and September days present low demand and high solar availability. The selected date in March has the highest wind availability and intermediate demand, and solar availability.

In this case study, it is assumed that all the energy is sold and bought in the DA market. Therefore, no long-term,

[4]In the game-theoretic literature, this is typically considered to be a measure of bounded rationality [6], [15]. Had complete information regarding the opponents been available, each ESS owner could then choose its bidding strategy based on a non-cooperative game structure facing other ESS owners, requiring the identification of the Nash equilibrium of that game. This structure goes beyond the scope of the current work.

[5]Since bilevel optimization problems are generally non-convex, the price-maker problem is reformulated as a mixed-integer linear programming (MILP) problem that could be solved using available solvers (e.g., GLPK in Julia [16]).

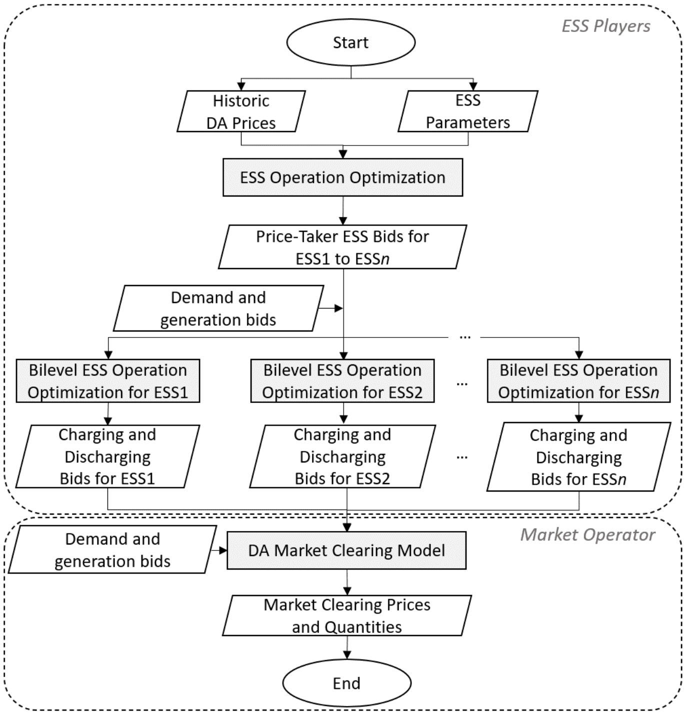

Fig. 2. Model methodology

intra-day, or real-time markets are included in the model. For simplification purposes, price bids from traditional units are considered to match their short-run marginal cost (SRMC) for producing electricity. Interconnection to the neighbouring bidding zones (i.e., the Netherlands (NL), France (FR), Germany/Luxembourg (DE-LU), and the United Kingdom (UK)) was included using historical flows. Specifically, a linear optimal power flow model is used to model the flows (and flow constraints) over the interconnections with neighbouring countries. The relevant constraints were added to (1)-(7) as proposed in [8]. All the assumptions and information used as input data for the case study were made available by the authors as supplementary material in [17].

A. Scenarios

Table A in the Appendix summarises the scenarios explored in the analysis. First, a ”baseline” scenario is used to assess the SEW effects of large-scale ESS given the 2019 energy mix. The supply and demand were modelled according to the information available on the website of the Belgian transmission system operator Elia [18] - further details are available in [17]. Subsequently, the 2019 generation mix was modified to represent a higher penetration of VRES as expected in 2030, hereafter referred to as ”large shares of VRES” scenario (LVRES). This change is expected given the European commitments to decarbonise the energy supply, reducing the greenhouse gas emissions. As such, the new generation mix was based on the “Large Scale RES” scenario proposed by Elia for 2030 [19].

To assess the inclusion of large-scale ESS, the baseline and LVRES scenarios described above are simulated with five storage levels: no storage, the existing PHES, and three different levels of ESS installed capacities, which are added considering three separately operated ESS. Belgium currently has a 1.3 GW capacity of PHES divided into two storage plants, Coo 1 & 2 and Plate Taille (i.e., two market players). For the no-storage scenario, all storage, including the existing PHES capacity, is removed from the model. For the low, medium, and high storage scenarios, the existing PHES capacity is modelled in addition to 100, 500, and 1000 MW of new storage capacity in the form of Lithium-ion BESS (i.e., three market players), respectively. Table B in the Appendix includes the parameters of the ESSs used in the model.

B. Effect of addition of price-maker large scale storage

The results of the simulation for all the considered scenarios are shown in Table I[6]. In most cases, adding large-scale storage resulted in a transfer of surplus from the producers to the consumers, due to higher off-peak prices and lower on-peak prices. While there is a gain for producers in off-peak profits because of the storage charging operations, this is offset by the drop in the producer’s on-peak profits, which tends to be larger because more energy is exchanged at these hours. However, this is not always the case, as seen in some of the analysed scenarios, such as the LVRES scenarios for June. Furthermore, it was found, in line with existing literature [20]–[22], that storage does not only redistribute the SEW by transferring part of the producer’s surplus to the consumers, but it also creates welfare by displacing high-cost generation with low-cost technologies, avoiding high MCPs.

The clearing of the Belgium market model showed that MCPs are highly influenced by solar and wind availability in the no storage case of the LVRES scenarios, as illustrated in Fig. 5 in the Appendix. In their study of the Spanish market, [21] found that this dependency of prices on stochastic resources increases price volatility, benefiting the storage arbitrage profits. However, in this case study of the Belgian DA market, the same result did not hold for the modelling dates with high wind availability (i.e., January and March) due to the relatively constant resource availability throughout the day, leading to limited arbitrage opportunities. Still, the ESS net revenues and SEW benefits for the LVRES scenarios were significantly higher than in the Baseline scenarios for the modelled days with high solar generation and low wind availability, such as June and September. This outcome showed that the addition of storage is especially valuable for summer days, where there is low wind and high solar availability.

As depicted in Table I, SEW tends to increase with the addition of storage capacity, since the presence of storage generally leads to less volatile market prices. As the number of players increases, the impact that each player has on the

[6]The entries marked with a star (*) correspond to cases in which the solver reached its time limit’s bounds while solving the price-maker problem for one of the ESS players. The best available (sub-optimal) solutions are, hence, reported.

TABLE I
DIFFERENCE IN SEW (Δ SEW), CONSUMER SURPLUS (Δ CS), PRODUCER SURPLUS (Δ PS), AND ESS REVENUE (Δ ESS R) UNDER THE PRICE-MAKER APPROACH. VALUES IN K€/DAY.

	Baseline				**LVRES**			
Storage Level	ΔSEW	ΔCS	ΔPS	$\Delta ESS\ R$	ΔSEW	ΔCS	ΔPS	$\Delta ESS\ R$
January								
Existing PHES	102.75	766.21	-722.12	58.66	16.2	28.41	-27.86	15.64
Low	108.69	1,294.69	-1,247.24	61.23	20.56	131.1	-129.75	19.21
Medium	117.01	2,314.56	-2,216.90	19.35	32.13	353.14	-334.31	13.29
High	136.85	3,424.92	-3,298.32	10.25	38.3	388.51	-346.8	-3.41
March								
Existing PHES	0.00*	0.00*	0.00*	0.00*	1.54	279.81	-279.25	0.97
Low	2.92	249.25	-248.46	2.14	2.15	0	0	2.15
Medium	6.7	724.74	-714.02	-4.01	-0.58	0	0	-0.58
High	0.54	689.01	-677.54	-10.93	-6.2	0	0	-6.2
June								
Existing PHES	23.56	1,231.90	-1,211.06	2.72	45.64	-569.52	584.59	30.58
Low	26.6	1,061.90	-1,038.78	3.48	52.9	-561.86	576.86	37.9
Medium	25.83	1,112.90	-1,082.98	-4.08	63.13*	645.13*	-569.74*	-12.26*
High	26.22*	1,304.32*	-1,255.19*	-22.91*	90.47*	-411.70*	433.24*	68.93*
September								
Existing PHES	0.5*	-2.8*	2.9*	0.4*	1,774.18	99,194.45	-97,724.29	304.02
Low	2.4	132.7	-130.6	0.2	1,817.07	104,886.36	-103,428.73	359.43
Medium	10.3*	190.8*	-186.1*	5.6*	1,707.16	86,932.03	-84,914.27	-310.6
High	6.6	754.5	-725.5	-22.4	1,777.13	87,840.53	-85,835.89	-227.51

price decreases, and therefore their market power, benefiting the overall SEW, a finding consistent with [23]. Nevertheless, this also results in lower potential arbitrage values from the use of storage and lower net storage revenues per installed MW. In the cases where the differences in on-peak and off-peak prices were small, such as the March baseline scenario, it was found that BESS were able to better capture the potential arbitrage value due to their higher efficiency. On the other hand, the PHES used little capacity or remained non-operational. Moreover, in those cases, a higher gain of SEW is obtained in the scenarios that include BESS technologies compared with the scenarios that only consider the existing PHES capacity.

C. Effect of ESS owner bidding strategy

The scenarios described in Table A were also modelled using only the price-taker approach. The results show a reduction in the added SEW obtained under the price-taker model when compared with results from the price-maker strategy, as shown in Table C (as compared to Table I). On the contrary, the added benefit for the other consumers or producers was greater for the price-taker case. This is because price-maker ESSs avoid decreasing the off-peak prices and decreasing the on-peak prices as much as possible in order to maintain a high arbitrage value, limiting additional surplus for other market players [23], [4], [3]. Moreover, since price-maker ESSs control their operation to obtain the maximum arbitrage value, results showed that price-maker ESSs made less use of their storage capacity and operated for shorter hours or fewer cycles than price-taker ESSs in an attempt to limit their effect on the high or low prices. An example of this result is illustrated in Fig. 4 in the Appendix.

IV. CONCLUSIONS AND FUTURE WORK

The results of the present work showcased a societal value in the energy arbitrage participation of large-scale ESS in the electricity markets, both in the current system and in a system with a large participation of VRES. For the latter, large-scale ESS participation is expected to have an essential role in levelling the prices caused by the daily cyclic variation in solar energy availability. Further, the results have shown that when acting strategically (as price-makers), ESS players tend not to use their full storage capacity to avoid reducing arbitrage value, limiting the amount of shifted energy and the SEW benefits. Therefore, it is important to explore market structures that incentivize the optimal system operation of large-scale ESS. Consequently, it is also recommended to develop mechanisms to incentivize competition between different storage merchants to achieve greater SEW benefits and avoid the concentration of market power.

This work lays the foundations for future research directions. In this regard, expanding the current analysis to larger geographical areas would provide an extended overview of the impact of large deployment of ESSs, especially considering varying interconnection capacities and VRES penetration in different interconnected countries. In addition, as addressed in Section 2, the current work can provide the foundation for an extended game-theoretic analysis of ESS market behaviour while considering different models of competition among ESS owners. Finally, given the unappealing ESS business case in the DA market, analysing the participation of ESSs in other market segments is a promising work direction for the future. In fact, the business case is expected to become more attractive for investors if the revenues from the participation in different markets are considered.

References

[1] IRENA, “Electricity storage and renewables: Costs and markets to 2030,” Tech. Rep., 2017.

[2] A. M. Elshurafa, “The value of storage in electricity generation: A qualitative and quantitative review,” *Journal of Energy Storage*, vol. 32, p. 101872, dec 2020.

[3] T. Brijs, F. Geth, C. De Jonghe, and R. Belmans, “Quantifying electricity storage arbitrage opportunities in short-term electricity markets in the CWE region,” *Journal of Energy Storage*, vol. 25, p. 100899, oct 2019.

[4] R. Sioshansi, P. Denholm, T. Jenkin, and J. Weiss, “Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects,” *Energy Economics*, vol. 31, no. 2, pp. 269–277, mar 2009.

[5] B. Nyamdash and E. Denny, “The impact of electricity storage on wholesale electricity prices,” *Energy Policy*, vol. 58, pp. 6–16, jul 2013.

[6] C. F. Camerer, T. H. Ho, and J. K. Chong, “A Cognitive Hierarchy Model of Games,” *The Quarterly Journal of Economics*, vol. 119, no. 3, pp. 861–898, aug 2004.

[7] T. Başar and G. J. Olsder, *Dynamic noncooperative game theory*. SIAM, 1998.

[8] M. Z. J. Morales, A. Conejo, H. Madsen, P. Pinson, *Integrating Renewables in Electricity Markets*, 1st ed. Springer US, 2014.

[9] EPEX. (2022) Trading Products at EPEX SPOT. [Online]. Available: https://www.epexspot.com/en/tradingproducts

[10] H. Le Cadre, “On the efficiency of local electricity markets,” *International Conference on the European Energy Market, EEM*, jul 2017.

[11] A. Sinha, P. Malo, and K. Deb, “A Review on Bilevel Optimization: From Classical to Evolutionary Approaches and Applications,” *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 2, pp. 276–295, apr 2018.

[12] A. Sanjab and W. Saad, *Power System Analysis: Competitive Markets, Demand Management, and Security*. Springer International Publishing, 2017, pp. 1–38.

[13] ——, “Data Injection Attacks on Smart Grids with Multiple Adversaries: A Game-Theoretic Perspective,” *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 2038–2049, jul 2016.

[14] G. de Clippel, R. Saran, and R. Serrano, “Level-*k* Mechanism Design,” *Review of Economic Studies*, vol. 86, no. 3, pp. 1207–1227, 2019.

[15] A. Sanjab and W. Saad, “On bounded rationality in cyber-physical systems security: Game-theoretic analysis with application to smart grid protection,” *IEEE Proceedings of the 2016 Joint Workshop on Cyber-Physical Security and Resilience in Smart Grids, CPSR-SG 2016*, oct 2016.

[16] A. O. Makhorin. (2000) GLPK - GNU Project - Free Software Foundation (FSF). [Online]. Available: https://www.gnu.org/software/glpk/

[17] E. Rocha Ojeda, L. Silva-Rodriguez, E. Fumagalli, A. Sanjab, and Madeleine, “Modelling assumptions and input dataset for the case study of the paper ”Societal Effects of Large-Scale Energy Storage in the Current and Future Day-Ahead Market: A Belgian Case Study”,” jul 2022. [Online]. Available: https://zenodo.org/record/6806409

[18] Elia. (2019) Grid data.

[19] ——, “Electricity Scenarios for Belgium Towards 2050,” Tech. Rep., 2017.

[20] R. Sioshansi, “Welfare impacts of electricity storage and the implications of ownership structure,” *The Energy Journal*, vol. 31, no. 2, pp. 173–198, 2010.

[21] D. Andrés-Cerezo and N. Fabra, “Storing power: Market structure matters,” Energy Policy Research Group, University of Cambridge, Tech. Rep., 2020.

[22] X. He, W. Delarue, E. abd D’Haeseleer, and J. Glachant, “Coupling electricity storage with electricity markets: a welfare analysis in the french market,” *KU Leuven (Working Paper)*, 2012.

[23] R. Sioshansi, “Welfare impacts of electricity storage and the implication of ownership structure,” *The Energy Journal*, vol. Volume 31, pp. 173–198, 04 2010.

[24] M. Irfan, Z.-Y. Zhao, M. Ahmad, and M. C. Mukeshimana, “Critical factors influencing wind power industry: A diamond model based study of india,” *Energy Reports*, vol. 5, pp. 1222–1235, 2019.

[25] S. Pfenninger and I. Staffell, “Long-term patterns of european pv output using 30 years of validated hourly reanalysis and satellite data,” *Energy*, vol. 114, pp. 1251–1265, 2016.

[26] F. Geth, T. Brijs, J. Kathan, J. Driesen, and R. Belmans, “An overview of large-scale stationary electricity storage plants in Europe: Current status and new developments,” *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 1212–1227, dec 2015.

[27] G. Limpens and H. Jeanmart, “Electricity storage needs for the energy transition: An EROI based analysis illustrated by the case of Belgium,” *Energy*, vol. 152, pp. 960–973, jun 2018.

V. Appendix

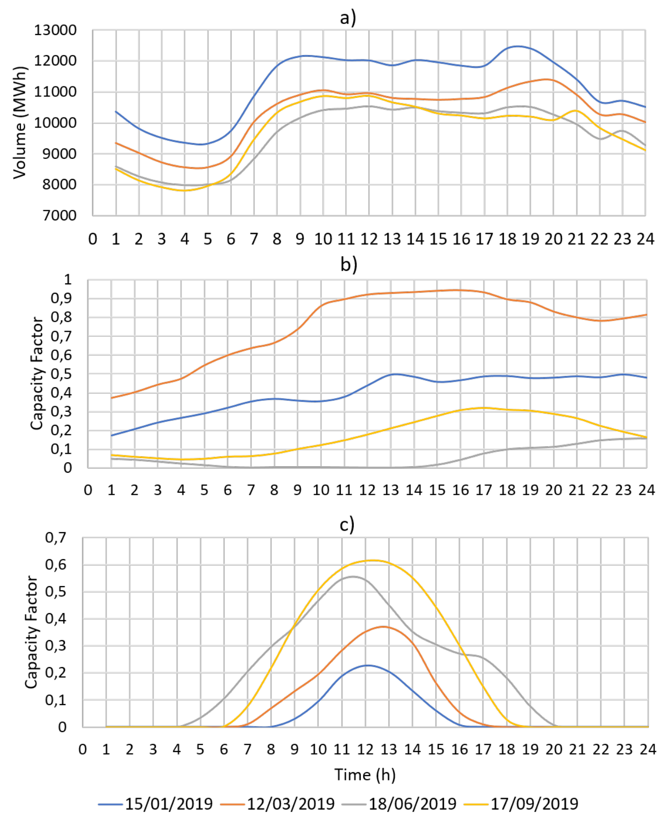

Fig. 3. Input data considered for the selected representative days: (a) Demand [18], (b) Wind generation [24] (c) Solar generation [25]

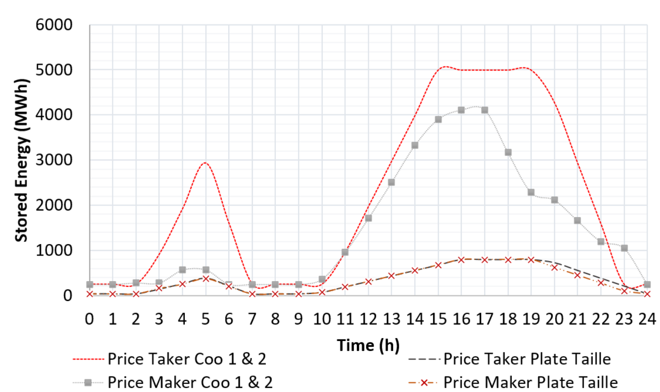

Fig. 4. Comparison of price-maker and price-taker ESS operation for September in the Baseline scenario with Existing PHES

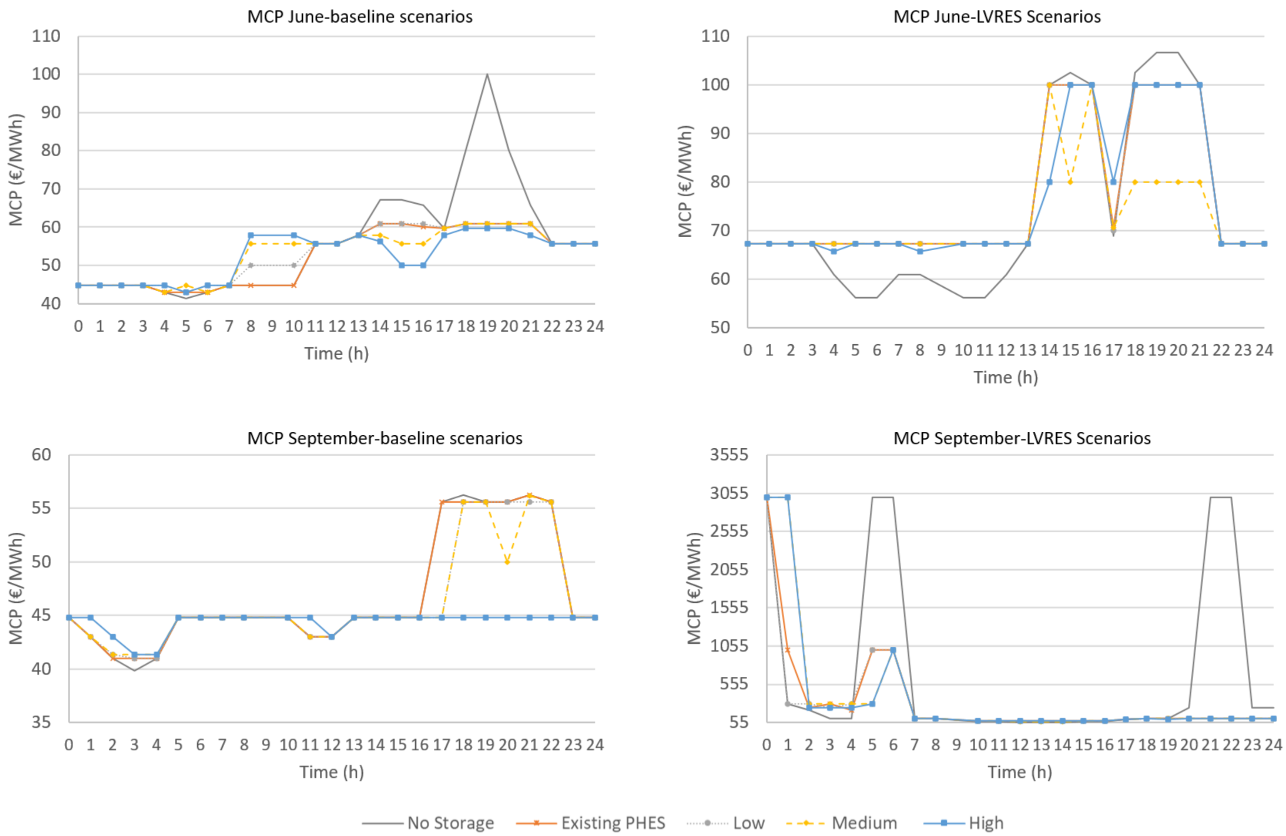

Fig. 5. MCP for the representative days in June and September

TABLE A
MODELLING SCENARIOS DESCRIPTION

Scenario name	VRES penetration	Storage/No storage	Active storage	Total storage capacity [MW]
Baseline no storage	27% of total installed capacity	No storage	None	0
Baseline existing PHES		Existing PHES	Coo 1&2 and Plate Taille	1300
Baseline low		Existing PHES + BESS storage	Coo 1&2, Plate Taille, and ESS1	1300 + 100
Baseline medium			Coo 1&2, Plate Taille, ESS1, and ESS2	1300 + 500
Baseline high			Coo 1&2, Plate Taille, ESS1, ESS2, and ESS3	1300 + 1000
LVRES no storage	64.5% of total installed capacity	No storage	None	0
LVRES existing PHES		Existing PHES	Coo 1&2 and Plate Taille	1300
LVRES low		Existing PHES + BESS storage	Coo 1&2, Plate Taille, and ESS1	1300 + 100
LVRES medium			Coo 1&2, Plate Taille, ESS1, and ESS2	1300 + 500
LVRES high			Coo 1&2, Plate Taille, ESS1, ESS2, and ESS3	1300 + 1000

TABLE B
PARAMETERS OF ESS USED FOR MODELLING

-	Rated active power	Rated energy storage	Initial state of charge	Recomm. depth of discharge	η_{ch}	η_{dis}	Ref.
Unit	*MW*	*MWh*	*%*	*ratio*	*ratio*	*ratio*	*N/A*
Coo1 & 2	1164	5000	5%	0.95	0.87	0.87	[19], [26]
Plate Taille	144	796	5%	0.95	0.84	0.84	
BESS 1	100	400	10%	0.9	0.95	0.95	[1], [27]
BESS 2	400	1200	10%	0.9	0.95	0.95	
BESS 3	500	2000	10%	0.9	0.95	0.95	

TABLE C
DIFFERENCE IN SEW (Δ SEW), CONSUMER SURPLUS (Δ CS), PRODUCER SURPLUS (Δ PS), AND ESS REVENUE (Δ ESS R) UNDER THE PRICE-TAKER APPROACH. VALUES IN K€/DAY.

	Baseline				**LVRES**			
Storage Level	**ΔSEW**	**ΔCS**	**ΔPS**	**ΔESS R**	**ΔSEW**	**ΔCS**	**ΔPS**	**ΔESS R**
				January				
Existing PHES	48.25	1,293.24	-1,175.15	-69.83	-10.98	426.22	-366.01	-71.19
Low	45.82	1,317.26	-1,185.59	-85.85	-12.54	368.7	-305.87	-75.37
Medium	15.09	1,726.28	-1,534.78	-176.41	-34.48	147.48	-26.7	-155.26
High	-114.57	-1,137.24	1,672.81	-650.13	-102	-504.56	801.49	-398.93
				March				
Existing PHES	-66.87	-117.85	159.28	-108.31	-34.83	-285.02	290.87	-40.68
Low	-72.17	-76.84	123.63	-118.96	-37.92	-285.02	290.87	-43.78
Medium	-105.56	-296.49	378.02	-187.09	-50.3	-285.02	290.87	-56.15
High	-191.56	-1,134.30	1,364.75	-422	-68.28	126.42	-87.26	-107.45
				June				
Existing PHES	-5.94	766.73	-691.98	-80.69	-115.11	-466.97	695.43	-343.57
Low	-14.42	822.01	-705.93	-130.5	-135.52	-451.14	728.57	-412.94
Medium	-65.69	144.7	32	-242.39	-254.5	-2,463.78	3,084.35	-875.07
High	-177.04	-405.43	735.96	-507.57	-1,572.16	-34,547.57	40,590.19	-7,614.78
				September				
Existing PHES	-177.96	-649.88	774.46	-302.53	-4,747.66	52,812.24	-47,122.93	-10,436.97
Low	-193.68	-712.23	846.48	-327.93	-5,395.32	52,782.27	-47,089.59	-11,087.99
Medium	-256.07	-1,530.09	1,802.49	-528.47	-7,997.44	53,785.46	-47,923.91	-13,858.99
High	-424.72	-3,840.85	4,542.97	-1,126.84	-11,306.69	54,113.75	-48,145.86	-17,274.58