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Battery Storage Energy Arbitrage Under Stochastic Dominance Constraints: A New Benchmark Selection Approach

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Abstract—**This paper presents an energy arbitrage strategy of a lithium-ion Battery Storage System (BSS) in sequential Day-ahead and Intraday (DA+INT) markets, considering its Cycle Aging Cost (CAC). One of the critical queries of the BSS in such problems is how to tackle the risk of uncertain prices in both market floors. Towards this end, a financial risk management method, i.e., Second-Order Stochastic Dominance Constraints (SOSDCs), is used to control the risk of uncertain market prices. Despite the promising performance of the SOSDCs over a broad range of decision-making problems, the primary challenge for decision-makers taking advantage of this approach is the selection of the minimum profit threshold. To effectively overcome this obstacle, this paper proposes a new benchmark selection approach based on a fuzzy decision-making manner over in-sample and out-of-sample analyses. The idea behind considering both in-sample and out-of-sample studies lies in an unforeseen change of the results by setting various benchmarks in SOSDCs. In this regard, to precisely formulate this problem, with an eye on the battery CAC, a linear two-stage stochastic framework is suggested. The numerical results show the applicability of the developed approach in benchmark selection for the SOSDCs.**

Keywords— Arbitrage, Battery Storage System (BSS), Benchmark Selection, Cycle Aging Cost (CAC), Stochastic Dominance Constraints.

I. Introduction

Battery Storage Systems (BSSs), from grid-scale to small-scale home applications, have evolved into an indivisible sector of today's electricity industry. Facilitating the operation of renewable energy sources, enhancing the total system's flexibility, and postponing expansion planning can be named as the most tangible benefits of BSSs. From a different perspective, several batteries, especially electrochemical ones, sustain degradation issues [1]. The degradation process of batteries mainly arises from multifarious discharging/charging cycles, which ultimately limits their lifespan [2]. In such situations, adopting suitable strategies to restrict degradation is critical [3]. Two comprehensive surveys on the degradation and aging of lithium-ion batteries as one of the most well-known electrochemical batteries have been conducted in [3] and [4].

In view of the above, the scheduling problem of BSSs considering BSS's degradation or Cycle Aging Costs (CACs) has received remarkable attention in recent years. In [5], the optimal scheduling of a typical microgrid considering the degradation of energy storage facilities by means of a model predictive control has been proposed. Ref. [6] has introduced a suitable energy management framework for plug-in electric vehicles while entering their degradation cost into the model. Similarly, the optimal energy management of a microgrid taking into account battery swapping stations has been developed in [7].

Next to these centralized models wherein BSSs are managed by a single agent, BSSs and other market players operating in competitive environments must design appropriate self-scheduling [8] or arbitrage strategies in electricity markets to get the highest possible profit. In [9], a stochastic optimization model has been established for a BSS paired with photovoltaic and thermal units participating in the energy market. In [10], the authors have proposed a data-driven arbitrage strategy for a BSS in energy and reserve markets using a bi-level programming approach. In [11], a robust optimization model was developed for the operating strategy of a hybrid battery-thermal system. Authors in [12]-[13] have suggested stochastic-interval architectures for the self-scheduling of a BSS along with intermittent and dispatchable generation units. In [14], the effect of the battery life's on the operating strategy of a BSS in day-ahead energy and ancillary services markets has been investigated. Ref. [15] has studied the impact of degradation costs on an electric vehicle aggregator's optimal offering and bidding strategies in energy and reserve markets. Ref. [16] has focused on elaborating on a precise CAC model for electrochemical batteries taking part in energy and reserve markets. In [17], the authors have extended the CAC model suggested in [16] for the participation of BSSs and electric vehicles in regulation markets. The bidding strategy of BSSs in the regulation markets considering CAC based on a chance-constrained stochastic programming framework has been presented in [18]. In [19], the authors have suggested a novel CAC function for modeling the degradation of a BSS optimizing its scheduling in energy and reserve markets. The authors of Ref. [20] have studied the impact of BSS degradation cost on the coordinated operation strategy of a wind-BSS system using a stochastic programming approach. A proper degradation model for the lithium-ion batteries has

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been provided in [21], while its effectiveness has been tested on a typical BSS offering regulation services in the PJM electricity market.

Motivated by these recent investigations [5]-[21], we concentrate on offering a new risk-aware scheduling model for the optimal arbitrage strategy of a large-scale lithium-ion battery in sequential Day-Ahead and Intraday (DA+INT) markets, taking into consideration the CACs. The proposed approach is built on Second-Order Stochastic Dominance Constraints (SOSDCs) with the goal of efficiently accounting for market uncertainties. The formulation of the proposed SOSDCs-based strategy is cast as two-stage mixed-integer programming. Since selecting the minimum profit threshold (i.e., benchmark selection) in most SOSDCs-based problems is a challenging task, in this paper, we focus on presenting a new benchmark selection approach which built over in-sample and out-of-sample studies. Finally, to attain the final optimal benchmark, the fuzzy decision-making pattern is used. The fuzzy decision-making manner assists the BSS in ascertaining the best attainable strategy in light of in-sample and out-of-sample studies. Briefly, the contributions of this paper are twofold:

- Presenting a SOSDCs-based arbitrage strategy for a large-scale BSS in DA+INT markets considering the CACs.
- Proposing a new benchmark selection approach based on in-sample and out-of-sample studies in a SOSDCs-based problem.

The remainder of this paper is organized as follows. The two-stage stochastic arbitrage strategy of the BSS considering CACs is presented in Section 2. Section 3 provides the SOSDCs-based framework of the model proposed in Section 2. Section 4 introduces the suggested benchmark selection approach. In Section 5, the developed methodology is tested for a large-scale BSS acting in the Spanish markets, and lastly, Section 6 gives the conclusions and future efforts.

II. Two-Stage Arbitrage Strategy of the BSS Considering its CACs

The notation utilized throughout the paper is introduced below.

Indices

$b.b'$	Benchmark scenarios in SOSDCs, from 1 to B.
s	Segments related to the linearized CAC function, from 1 to S.
t	Time periods, from 1 to T.
ω	Scenarios of uncertain sources, from 1 to Ω.

Parameters

$k_b.k_{b'}$	BSS benchmark profit in SOSDCs for scenarios b and b' [€].
α	Coefficient limiting the intraday charge and discharge powers.
$\sigma_{t.\omega}^{DA}$	DA market price [€/MWh].
$\sigma_{t.\omega}^{IN}$	Intraday market price [€/MWh].
τ^{SoC}	Maximum BSS energy state-of-charge [MWh].
$\grave{u}_s^{SoC}$	Maximum BSS allowable energy state-of-charge in block s of depth-of-discharge [MWh].
τ^{dis}	Maximum BSS discharge power [MW].
τ^{ch}	Maximum BSS charge power [MW].
Λ^{dis}	Discharge efficiency of the BSS.
Λ^{ch}	Charge efficiency of the BSS.
ψ_s	Marginal CAC in segment s of the linearized CAC function.
π_ω	Scenario ω probability.
$\eta_b.\eta_{b'}$	Scenario b and b' probabilities.

Variables

$\rho_t^{DA.dis}$	BSS discharge power to the DA market [MW].
$\rho_t^{DA.ch}$	BSS charge power from the DA market [MW].
$\rho_{t.\omega}^{dis.IN}$	BSS discharge power to the intraday market [MW].
$\rho_{t.\omega}^{ch.IN}$	BSS charge power from the intraday market [MW].
$\rho_{s.t}^{dis.DA}$	BSS DA discharge power from segment s of depth-of-discharge [MW].
$\rho_{s.t}^{ch.DA}$	BSS DA charge power from segment s of depth-of-discharge [MW].
$\rho_{s.t.\omega}^{dis.IN}$	BSS discharge power from segment s of depth-of-discharge [MW].
$\rho_{s.t.\omega}^{ch.IN}$	BSS charge power from segment s of depth-of-discharge [MW].
$\Delta_{t.\omega}^{SoC}$	BSS energy state-of-charge [MWh].
$\delta_{s.t.\omega}^{SoC}$	BSS energy state-of-charge in segment s of depth-of-discharge [MWh].
ε_t	Binary decision variable for modeling the discharging mode of the BSS.
$\zeta_{\omega.b}$	Continiuous variable used in SOSDCs [€].

In this paper, the optimal arbitrage strategy of a lithium-ion BSS in DA+INT markets is established. Lithium-ion batteries offer numerous benefits over other classes of battery technology, from grid-scale to small-scale home applications. The high energy density and relatively low self-discharge rate are among its most substantial advantages, while aging issues can be identified as its most critical drawback. Accordingly, a broad range of scientific works has been devoted to addressing the aging problem of lithium-ion batteries, as expressed in the introduction. Amid all the models proposed in the literature, the architecture suggested in [16] is employed in this work to account for the CACs of the BSS. Based on [16], the CACs of a lithium-ion battery can be expressed as a near-quadratic function of the depth-of-discharge. To keep the process linear, the CAC function is approximated by piecewise linear segments [16]. Based on this CAC modeling, the BSS arbitrage strategy in DA+INT markets can be efficiently modeled as a two-stage stochastic problem, whereas the day-ahead and intraday decisions are the first- and second-stage decisions [22]. Following the preceding, the objective function of the BSS in such framework can be expressed as (1):

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$$\text{Max} \quad \sum_{\omega=1}^{\Omega} \pi_w \sum_{t=1}^{T} (\sigma_{t.\omega}^{DA} [\rho_t^{DA.dis} - \rho_t^{DA.ch}]) + (\sigma_{t.\omega}^{IN} [\rho_{t.\omega}^{IN.dis} - \rho_{t.\omega}^{IN.ch}]) - (\sum_{s=1}^{S} \psi_s [\rho_{s.t}^{DA.dis} + \rho_{s.t.\omega}^{In.dis}]) \tag{1}$$

where the terms in the first and second parentheses represent the lithium-ion battery's revenue and expense emanating from discharge and charge processes in DA+INT markets, while the third term accounts for the CACs. Note that the CAC curve is monotonically increasing. The constraints associated with (1) are presented below [16], [23]-[24]:

$$\rho_t^{DA.dis} = \sum_{s=1}^{S} \rho_{s.t}^{DA.dis} \quad \forall t \tag{2}$$

$$\rho_t^{DA.ch} = \sum_{s=1}^{S} \rho_{s.t}^{DA.ch} \quad \forall t \tag{3}$$

$$\rho_{t.\omega}^{IN.dis} = \sum_{s=1}^{S} \rho_{s.t.\omega}^{IN.dis} \quad \forall t. \forall \omega \tag{4}$$

$$\rho_{t.\omega}^{IN.ch} = \sum_{s=1}^{S} \rho_{s.t.\omega}^{IN.ch} \quad \forall t. \forall \omega \tag{5}$$

$$0 \le \rho_t^{DA.dis} \le \tau^{dis} \varepsilon_t \quad \forall t \tag{6}$$

$$0 \le \rho_t^{DA.dis} + \rho_{t.\omega}^{IN.dis} \le \tau^{dis} \varepsilon_t \quad \forall t. \forall \omega \tag{7}$$

$$0 \le \rho_t^{DA.ch} \le \tau^{ch} (1 - \varepsilon_t) \quad \forall t \tag{8}$$

$$0 \le \rho_t^{DA.ch} + \rho_{t.\omega}^{IN.ch} \le \tau^{ch} (1 - \varepsilon_t) \quad \forall t. \forall \omega \tag{9}$$

$$0 \le \rho_{t.\omega}^{IN.dis} \le \alpha \rho_t^{DA.dis} \quad \forall t. \forall \omega \tag{10}$$

$$0 \le \rho_{t.\omega}^{IN.ch} \le \alpha \rho_t^{DA.ch} \quad \forall t. \forall \omega \tag{11}$$

$$\rho_{s.t}^{DA.dis} . \rho_{s.t}^{DA.ch} . \rho_{s.t.\omega}^{IN.dis} . \rho_{s.t.\omega}^{IN.ch} \ge 0 \quad \forall t. \forall \omega \tag{12}$$

$$\delta_{s.t.\omega}^{SoC} = \delta_{s.t-1.\omega}^{SoC} - \left(\frac{\rho_{s.t}^{DA.dis} + \rho_{s.t.\omega}^{IN.dis}}{\Lambda^{dis}} \right) + (\Lambda^{ch} [\rho_{s.t}^{DAch} + \rho_{s.t.\omega}^{IN.ch}]) \quad \forall s. \forall t. \forall \omega \tag{13}$$

$$\Delta_{t\omega}^{SoC} = \sum_{s=1}^{S} \delta_{s.t.\omega}^{SoC} \quad \forall t. \forall \omega \tag{14}$$

$$0 \le \delta_{s.t.\omega}^{SoC} \le \grave{u}_s^{SoC} \quad \forall s. \forall t. \forall \omega \tag{15}$$

$$0 \le \Delta_{t.\omega}^{SoC} \le \tau^{SoC} \quad \forall t. \forall \omega \tag{16}$$

Constraints (2)-(5) express that the discharge and charge powers of the BSS in DA+INT markets are equal to the sum of the discharge and charge powers in every segment of depth-of-discharge. Constraints (6)-(9) ensure that the discharge and charge powers in DA+INT markets are scheduled without violating their operating bounds. Constraints (10) and (11) limit intraday discharge and charge powers, respectively. Restriction (12) enforces that DA+INT discharge and charge powers in every segment of the depth-of-discharge must take positive values. The energy state-of-charge in every segment of the depth-of-discharge is computed by (13), while equation (14) expresses the final state-of-charge of the BSS. Constraints (15) and (16) are used to impose acceptable boundaries for energy state-of-charge. The first-stage decisions are $\rho_{s.t}^{DA.dis}$, $\rho_{s.t}^{DA.ch}$, $\rho_t^{DA.dis}$, $\rho_t^{DA.ch}$, and ε_t, while the second-stage decisions are $\rho_{s.t.\omega}^{IN.dis}$, $\rho_{s.t.\omega}^{IN.ch}$, $\rho_{t.\omega}^{IN.dis}$, $\rho_{t.\omega}^{IN.ch}$, $\delta_{s.t.\omega}^{SoC}$, and $\Delta_{t.\omega}^{SoC}$.

III. SOSDCs-Based Arbitrage Strategy of the BSS

The DA+INT market prices are volatile and uncertain and should not be treated as deterministic parameters. Consequently, to elaborate a proper strategy for the involvement of the BSS in the DA+INT markets, a fitting uncertainty characterization method must be adopted [25]. In this work, stochastic scenarios are utilized to deal with these uncertainties [22], [26]. However, mere characterization of uncertainties does not suffice decision-makers. They need to assess the risk of uncertainties for efficient decision-making. Various risk assessment methods have been suggested to cope with the risk of stochastic scenarios in the literature. Among them, stochastic dominance is an engaging risk controlling method that aims for satisfactory solutions (by imposing pre-given benchmark) instead of directly seeking the best solution (profit) [27]. Accordingly, the stochastic dominance approach assures that the resultant solution is greater than the pre-specified benchmark. Stochastic dominance encompasses various models such as first- and second-order stochastic dominance approaches, while the first-order one has received less attention due to its non-convexity. The SOSDCs are thus utilized in this paper to handle the existing risk. The SOSDCs-based formulation of the BSS arbitrage problem is formulated as follows:

$$\text{Max} \quad \sum_{\omega=1}^{\Omega} \pi_w \sum_{t=1}^{T} (\sigma_{t.\omega}^{DA} [\rho_t^{DA.dis} - \rho_t^{DA.ch}]) + (\sigma_{t.\omega}^{IN} [\rho_{t.\omega}^{IN.dis} - \rho_{t.\omega}^{IN.ch}]) - (\sum_{s=1}^{S} \psi_s [\rho_{s.t}^{DA.dis} + \rho_{s.t.\omega}^{In.dis}]) \tag{17}$$

Subject to:

$$\sum_{t=1}^{T} \sigma_{t.\omega}^{DA} [\rho_t^{DA.dis} - \rho_t^{DA.ch}] + \sigma_{t.\omega}^{IN} [\rho_{t.\omega}^{IN.dis} - \rho_{t.\omega}^{IN.ch}] - \sum_{s=1}^{S} \psi_s [\rho_{s.t}^{DA.dis} + \rho_{s.t.\omega}^{In.dis}] \ge k_b - \zeta_{\omega.b} \quad \forall \omega. \forall b \tag{18}$$

$$\sum_{\omega=1}^{\Omega} \pi_w \zeta_{\omega.b} \le \sum_{b\prime=1}^{B} \eta_{b\prime} \times \max(k_b - k_{b\prime}. 0) \quad \forall b \tag{19}$$

$$\zeta_{\omega.b} \ge 0 \quad \forall \omega. \forall b \tag{20}$$

$$\text{Constraints} \quad (2) - (16) \tag{21}$$

The SOSDCs constraints are enforced by means of (18)-(20). In SOSDCs, we can consider different scenarios b for benchmark profit k_b while each of them has a specific probability η_b. Note that $\zeta_{\omega.b}$ is a continuous variable computing the profit deficit below the pre-given benchmark [27].

IV. Proposed Benchmark Selection Approach in SOSDCs

Despite the extensive benefits mentioned for the SOSDCs in related works, the greatest challenge in this risk

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assessment method is proper benchmark selection. While a broad spectrum of relevant studies has chosen benchmarks based on empirical analyses, in this work, we focus on benchmark selection from a more informed perspective. This paper concentrates on presenting a new benchmark selection approach founded on in-sample and out-of-sample studies. The reason behind proposing such a framework lies in the fact that each input benchmark in optimization problem (17)-(21) leads to a solution with different in-sample and out-of-sample results. Note that in-sample results are not sufficient to judge the performance of each entry benchmark. Consequently, an out-of-sample analysis is crucial to evaluate the performance of the chosen benchmark over a large number of scenarios. Having different in-sample and out-of-sample results concerning various entry benchmarks reveals the necessity of adopting a suitable pattern to find the final optimal strategy. To this end, the fuzzy decision-making pattern is applied. The algorithm of the proposed benchmark selection approach is given in Algorithm 1.

Algorithm 1 Benchmark Selection Approach

1: Derive in-sample scenarios for DA+INT prices following a scenario generation and reduction approach [28].

2: Derive out-of-sample scenarios for DA+INT prices following a scenario generation approach.

3: Solve problem (1)-(16) using obtained scenarios in step 1.

4: Select an initial benchmark k_b based on the obtained cumulative distribution function of the objective function in the previous step.

5: Solve SOSDCs-based problem (17)-(21) using obtained scenarios in step 1 and the selected benchmark. The results obtained in this step are called in-sample results.

6: Perform an out-of-sample study using generated scenarios in step 2 and the results obtained from step 5 [29]. The results obtained in this step are called out-of-sample results.

7: Update the entry benchmark using equation (22) and go back to step 5.

$$k_b = k_b + \theta \tag{22}$$

where θ represents the benchmark increment value. In fact, parameter θ controls the number of benchmarks that are going to be evaluated.

8: Iterate steps 5 to 7 until the desired number of benchmarks are evaluated.

9: Calculate membership functions of the in-sample and out-of-sample results for all entry benchmarks using equation (23).

$$\mu_{in/out}^{b} = \begin{cases} 0 & f_{in/out}^{b} \le f_{in/out}^{min} \\ \dfrac{f_{in/out}^{b} - f_{in/out}^{min}}{f_{in/out}^{max} - f_{in/out}^{min}} & f_{in/out}^{min} \le f_{in/out}^{b} \le f_{in/out}^{max} \\ 1 & f_{in/out}^{b} \ge f_{in/out}^{max} \end{cases} \tag{23}$$

where in/out refers to the in-sample or out-of-sample analysis and $f_{in/out}^{b}$ refers to the values of in-sample or out-of-sample profit in b th benchmark. $f_{in/out}^{max}$ and $f_{in/out}^{min}$ stand for the maximum and minimum values of in-sample or out-of-sample profit among all considered benchmarks. The higher the value of the membership function in each benchmark b, the higher the optimality degree.

10: Calculate the total optimality level of each considered benchmark with respect to the comparative significance of in-sample or out-of-sample profit ($w_{in/out}$) using equation (24).

$$\mu_{total}^{b} = \frac{w_{in}\mu_{in}^{b} + w_{out}\mu_{out}^{b}}{w_{in} + w_{out}} \tag{24}$$

where μ_{total}^{b} is the total level of the optimally of each entry benchmark (total membership value). The greater values of this parameter reflect a higher level of optimality.

11: Eventually, the solution (benchmark) with the greatest quantity of μ_{total}^{b} is selected as the most desired solution.

V. Case Studies

In this section, the suggested SOSDCs-based arbitrage strategy is tested on a large-scale BSS with specifications listed in Table 1. All in-sample and out-of-sample scenarios of DA+INT prices are generated for the Spanish market on November 18th, 2019. For in-sample analysis, twenty scenarios are considered for each of DA+INT market prices, while one thousand scenarios are taken into account for the out-of-sample analysis. The scenario generation and reduction processes have been explained in [23], [28]. All data relating to the CAC of the considered lithium-ion BSS can be found in [16], while the CAC function is linearized using twenty segments. In this paper, we focus on the one-scenario benchmark in the proposed SOSDCs framework, so the probability of each considered benchmark is equal to 1. The established model was formulated as a mixed-integer programming problem and implemented in the General Algebraic Modeling System (GAMS) and solved with CPLEX. It has to be noted that in all simulations, the weighting factors of the in-sample and out-of-sample profits ($w_{in/out}$) are chosen as $w_{in} = 1$ and $w_{out} = 1$, respectively, implying that both analyses have the same degree of importance to the decision-maker.

TABLE I. DATA ON THE CONSIDERED BSS.

Parameter	Value	Unit
τ^{SoC}	175	MWh
τ^{dis}	35	MW
τ^{ch}	35	MW
Λ^{dis}	0.95	Constant
Λ^{ch}	0.95	Constant

According to Algorithm 4, we first solve the optimization problem (1)-(16). Based on the obtained cumulative distribution profit function, we, therefore, set $k_b =$ 1.416.23€ as the initial benchmark in the SOSDCs-based problem. Next, we set $\theta = 50$€ to thoroughly analyze the

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impact of different benchmarks on the developed risk-based model. Note that Algorithm 4 is terminated after reaching 10 different solutions. Table 2 displays the obtained solution sets for the SOSDCs-based scheduling of the BSS in the DA+INT markets. In Table 2, the first column shows the considered benchmarks. The next two columns represent the in-sample and out-of-sample profits, while the next two columns refer to in-sample and out-of-sample CACs. Finally, the last three columns describe the membership value of the in-sample and out-of-sample profits and the total membership value, respectively. Following the developed methodology, the seventh row of Table 2, which possesses the greatest quantity of μ_{total}^{b}, is chosen as the most favored strategy. It can be seen that the most favored benchmark among all considered ones is €1,666.23, yielding €2,770.66 and €2,841.05 in-sample and out-of-sample profits, respectively. According to Table 2, it is observed that the greater the benchmark, the lower the in-sample profit, as expected. In other words, the decision-maker reduces the associated risk by picking a greater benchmark and, as a result, achieving a lower in-sample profit. On the other hand, the performance of out-of-sample analysis is not a function of entry benchmarks. As observed, those scenarios with a lower in-sample profit result in greater out-of-sample profits. This reveals that the risk-averse solutions have a more solid performance in out-of-sample analysis, which is a reliable study to the decision-makers. Another critical point is the pretty close range of CACs in both in-sample and out-of-sample analyses.

Figs. 1 and 2 show DA+INT decisions of the BSS for the most favored solution designated in Table 2 ($k_b = 1{,}666.23$ €). From Figs. 1 and 2, it can be seen that discharging happens at hours 9, 17-21, while charging occurs at hours 1-6, 12. The greatest discharge powers in DA+INT markets take place at hours 21 and 19, respectively, as a consequence of having the highest market prices.

VI. Conclusion and Future Works

With the ever-increasing attention on lithium-ion batteries, proposing a suitable methodology for addressing their arbitrage strategy considering degradation issues is still one of the research priorities. In this regard, to target the arbitrage strategy of a large-scale lithium-ion battery in the DA+INT markets considering its CAC, a new SOSDCs-based technique was suggested in this paper. To fully take advantage of the promising characteristics of the SOSDCs model, we offered a new benchmark selection approach based on in-sample and out-of-sample studies, and consequently, the fuzzy decision-making pattern was exploited to attain the most favored strategy. The effectiveness of the suggested arbitrage model was validated by simulations. The simulation results revealed that: 1) the proposed method can find the most favored benchmark in SOSDCs among all considered benchmarks, and 2) a fair trade-off between in-sample and out-of-sample results aids decision-makers against the challenging benchmark selection task in SOSDCs-based problems. Future work focuses on the performance of the suggested approach versus deterministic, risk-neutral stochastic, and CVaR-based frameworks with a more advanced and detailed decision-making pattern.

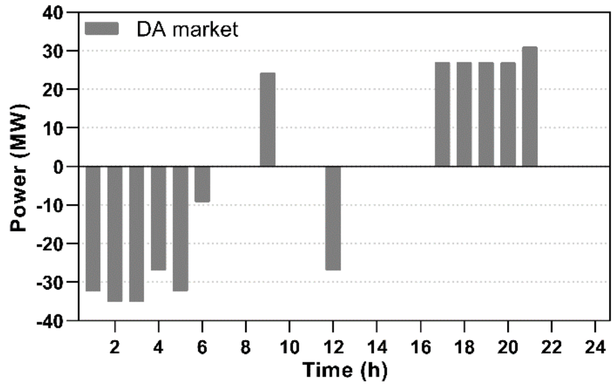

Fig. 1. DA charge and discharge powers in the most favored strategy.

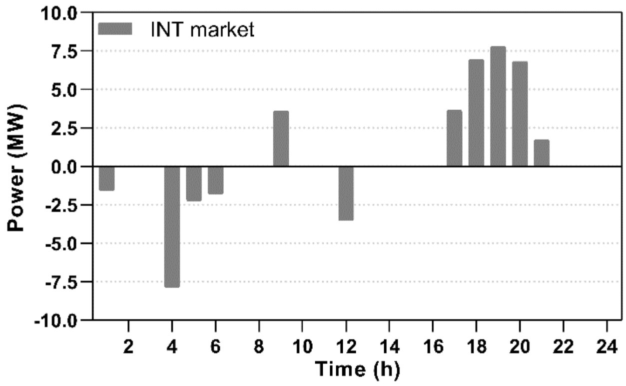

Fig. 2. INT charge and discharge powers in the most favored strategy.

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TABLE II. RESULTS OF THE DEVELOPED ALGORITHM FOR 10 DIFFERENT BENCHMARKS..

k_b [€]	In-Sample Analysis Profit [€]	Out-of-Sample Analysis Profit [€]	In-Sample Analysis CAC [€]	Out-of-Sample Analysis CAC [€]	μ_{in}^{b}	μ_{out}^{b}	μ_{total}^{b}
1,416.23	2,779.48	2,804.36	112.55	111.83	1.000	0.811	0.905
1,466.23	2,779.29	2,808.68	112.57	111.38	0.999	0.833	0.916
1,516.23	2,779.29	2,808.68	112.59	111.91	0.998	0.845	0.921
1,566.23	2,778.59	2,821.35	111.97	111.43	0.996	0.898	0.947
1,616.23	2,777.17	2,829.91	111.81	111.04	0.990	0.942	0.966
1,666.23	2,770.66	2,841.05	111.89	111.04	0.961	1.000	0.980
1,716.23	2,755.84	2,839.64	111.85	110.99	0.897	0.992	0.945
1,766.23	2,707.62	2,810.65	113.19	112.31	0.689	0.843	0.766
1,816.23	2,632.57	2,723.67	113.88	113.00	0.365	0.395	0.380
1,866.23	2,548.06	2,646.92	115.72	114.24	0.000	0.000	0.000