Optimal Battery Storage Arbitrage Considering Degradation Cost in Energy Markets

Alireza Akbari-Dibavar
Faculty of Electrical and
Computer Engineering
University of Tabriz
Tabriz, Iran
a.dibavar96@ms.tabrizu.ac.ir

Behnam Mohammadi-Ivatloo
Department of Enegy
Technology
Aalborg University
Aalborg, Denamrk
bmo@et.aau.dk

Amjad Anvari-Moghaddam
Department of Enegy
Technology
Aalborg University
Aalborg, Denamrk
aam@et.aau.dk

Sayyad Nojavan
Department of Electrical
Engineering
University of Bonab
Bonab, Iran
sayyad.nojavan@bonabu.ac.ir

Morteza Vahid-Ghavidel
Faculty of Engineering
University of Porto, and INESC
TEC
Porto, Portugal
mv.ghavidel@fe.up.pt

Miadreza Shafie-khah
School of Technology and
Innovations
University of Vaasa
Vaasa, Finland
mshafiek@univaasa.fi

João P. S. Catalão
Faculty of Engineering
University of Porto, and INESC
TEC
Porto, Portugal
catalao@fe.up.pt

Abstract— Energy arbitrage have monetary benefits for privately owned battery energy storage systems, such as the battery of an electric vehicle or residential batteries. However, the life cycle and degradation cost of the battery storage should be taken into consideration and can decrease obtained income in the long-term. This paper proposes an optimization framework to derive optimal bidding and offering curves for lead-acid battery storage participate in a stepwise energy market. The objective is to maximize the profit comes from participating in energy arbitrage action, while the life cycle of the battery is considered by objective function and constraints. Due to the small capacity of the considered storage unit, it can be assumed that this unit is a price-taker participant, which its actions cannot influence the market prices. Hence, the energy prices are modeled as uncertain parameters using stochastic programming approach. The second order stochastic dominance constraints are as risk management method.

Keywords— *Energy storage arbitrage, Lead-acid battery, life cycle, degradation cost, energy market*

Nomenclature

Symbols

t	Time index (h)
s, s', v, v'	Sets of scenarios
$\rho(s)$	The probability of each scenario
$\tau(v)$	The probability of benchmark scenario
$k(v)$	Considered benchmarks
$\pi(t,s)$	Electricity price at time t under scenario s ($/kWh)
$C_{\deg}$	LABS degradation cost ($/kWh)
C_{bat}	Cost of the battery ($/kWh)
L	Cycle life
L_{DOD}	Actual battery life (kWh)
DOD	The depth of discharging (%)
A, B	Degradation linear coefficients
η	LABS's efficiency (%)
E_{bat}	The total capacity of LABS (kWh)
$P^{ch}(t,s)$	Charged power at time t under scenario s (kW)
$P^{dis}(t,s)$	Discharged power at time t under scenario s (kW)
$u^{ch}(t,s)$	Binary variable indicating charging of LABS
$u^{dis}(t,s)$	Binary variable indicating discharging of LABS
$SOC(t,s)$	State-of-charge (SOC) of LABS at time t under scenario s (%)
$SOC_{\min}, SOC_{\max}$	Minimum and maximum of SOC (%)
SOC_{init}	Initial SOC of LABS at time $t=0$ (%)
SOC_{fin}	Final SOC of LABS at time $t=24$ (%)
$S(s,v)$	Decision variable of SOSD
LABS	Lead-acid battery storage

I. Introduction

Energy storage systems (ESSs) have many potential benefits for power system operators, their owners and energy consumers. Providing flexibility in the system operation, peak shaving, enhancing the power balance of the system in the presence of intermittent renewable-based sources and helping in frequency regulation, for instance [1]. One of the prominent features of the ESS is using price arbitrage in the power markets, which takes advantage of spot price changes in different periods and create inter-temporal transactions to gain monetary benefits by buying energy with low price, storing and selling it back to the market with the higher price. Compressed air energy storage (CAES),

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pumped hydro storage (PHS) and battery storage systems (BSS) have attracted more attention because of their high energy storing ability and they have appeared in grid-scale applications. For instance, the optimal bidding and offering of CAES merchant storage facility is investigated by [2]. Among battery technologies, different kind of battery storages, such as lead-acid, sodium-sulfur (Na-S), lithium-ion (Li-ion) and redox flow (RF) are utilized more for price arbitrage [3].

A. Literature review

The prevalence of plug-in electric vehicles (PEVs) and smart homes contain BSS have created an opportunity for the owners of these battery systems to participate in various power markets [4]. With this regard, different smart PEV charging algorithms in smart transactive actions from various view of points have been reviewed by [5]. BSSs and the battery of PEVs can also be helpful for grid frequency controlling, as they are well-known for fast-ramping capability. As main parts of smart grids, the optimal controlling of PEVs in providing frequency stability of a deregulated grid has been studied by [6]. In [7], the authors have proposed an optimal bidding strategy problem for the independent BESS investors to take part in energy markets and provide hourly bids and offers to maximize their profit. However, the focus of the paper is mainly concentrated on modeling the uncertainties of the market price using a hybrid uncertainty management technique. Modeling and formulation of cryogenic energy storage integrated with air separation unit in wind-integrated system is presented in [8]. The uncertainties are modeled using stochastic programming. In [9], the BESS is utilized for advantages of energy arbitrage and local power factor correction. From this paper, the profit of arbitrage for the BESS with fast ramping capability is significantly dependent on the affecting uncertainty such as electricity price. However, none of these recent works has not considered a comprehensive molding to consider negative impacts of BESS cycling and degradation on the performance of the BESS operation. Although, the frequent charging and discharging of the BSS can enhance the income of energy arbitrage or frequency regulation transactions, but has a negative impact on the life of the BSS and consequently has a substantial negative impact on profitability. The authors of [10] have shown that although degradation cost consideration can decrease the revenue in short-term, this reduction will be compensated by the long life of BSS.

Regarding merchant energy storage systems, the economics of utilizing energy storage system in energy and regulation services considering degradation cost have been studied by [11]. The degradation cost is calculated based on cost of storage over its lifetime. The lifetime of storage is assessed based on depth of discharge (DOD) and cycling of energy. The optimal capacity allocation between energy arbitrage and operating reserve provision is discussed in [12], with considering cycle life and degradation model of a simulated BSS. The authors divide degradation costs into two subcategories: i) life degradation, and ii) capacity degradation or fading. The life degradation is caused by the number of charging/discharging cycling of BSS and corresponding DOD, while capacity degradation means that the useful capacity of battery is decreased over time by battery operation can be modeled by linear or exponential functions.

The optimal bidding strategy of a wind-BSS system in real-time energy markets considering the degradation of BSS is studied in [13]. The degradation model is integrated to the hybrid deterministic/stochastic optimization. The authors have expressed that the degradation model of BSS is consist of two parts. The first is constant and regardless of BSS cycling reputed to shelf degradation. The second part of the model is proportioned to the cycling behavior of the BSS. The degradation of BSS is set to the maximum amount among two mentioned parameters. The performance and viability of operation of BESS in automatic Frequency Restoration Reserve markets has been studied in [14]. The cost of aging of the BESS is considered using semi-empirical formulations that divide the degradation model into two elements, namely calendar component and cyclic component. The optimal bidding strategy of BSS in power markets, including energy, spinning reserve, and regulation markets, intertwined with BSS cycle life model is proposed by [15]. The authors believed that the profitability of BSS is a function of its life time and under various operation strategies, the cycle life of BSS is computed. The optimal energy arbitrage of BSS in the presence of price uncertainty and considering non-linear relation between BSS aging and operational parameters is presented in [16]. The model is represented as mixed-integer non-linear programming and for solving efficiently dynamic programming is proposed. In [17], the problem of BESS arbitrage considering an effective degradation model of the BESS is addressed using a reinforcement learning approach. The mentioned approach was implemented to learn charging/discharging control strategies.

It should be mentioned that the number of technical literatures investigating the optimal scheduling of BSS in power markets with various and complex degradation and lifecycle models is not few; however, in comparison with existed works, this paper provides straightforward mathematical modeling of LABS degradation considering lifetime and cycling of BSS, which easily can be used by the BSS owners. The presented optimization derives optimal bidding and offering curves for stepwise energy markets. In the stepwise energy markets, the participants can submit their offers and bids in one or more blocks. Considering uncertainties exist in the market clearing process, such as load variation, intuitively, bidding and offering with more than one block can be recommended for BSS, since it increases the probability of its commission in the market. In this paper, stochastic programming is adopted to generate bidding/offering blocks using electricity price scenarios. Based on these blocks, the LABS provides optimal decisions in the energy arbitrage market.

The rest of the paper is organized as follows: in Section II, the mathematical problem formulation of LABS arbitrage, its physical constraints and lifecycle calculation are presented. The data and results are shown and discussed in Section III. In Section IV, the conclusion is presented.

II. PROBLEM FORMULATION

A. Risk-neutral problem

In this paper, the income of the LABS is defined as the difference between the discharged and charged powers multiplied by the corresponding hourly energy prices. Equation (1) shows that the objective function aims to maximize the

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expected profit, which consists of two parts. The first part in the bracket describes the revenue of the LABS participates in energy markets and takes the advantage of energy arbitrage, while the second part's item models the degradation cost of the LABS, which is linked to total energy changing of LABS [18]. Decision variables are P^{ch}, P^{dis}, u^{ch}, u^{dis}, SOC, DOD, L, L_{DOD}, and C_{deg}.

$$Max \quad \sum_{t}\sum_{s}\rho(s)\times\begin{Bmatrix}(P^{dis}(t,s)-P^{ch}(t,s))\times\pi(t,s)\\-C_{\deg}\times(P^{ch}(t,s)+P^{dis}(t,s))\end{Bmatrix}$$
(1)

$$DOD=\sum_{t}\sum_{s}\rho(s)\times\begin{bmatrix}\dfrac{P^{ch}(t,s)\times\left|u^{ch}(t,s)-u^{ch}(t-1,s)\right|}{\eta\times E_{bat}}\\+\dfrac{P^{dis}(t,s)\times\left|u^{dis}(t,s)-u^{dis}(t-1,s)\right|}{\eta\times E_{bat}}\end{bmatrix}$$
(2)

$$L = A \times DOD + B \tag{3}$$

$$L_{DOD} = E_{bat} \times L \tag{4}$$

$$C_{deg} = \frac{C_{bat}}{L_{DOD}} \tag{5}$$

$$0 \le P^{ch}(t,s) \le 0.5 \times E_{bat} \times u^{ch}(t,s) \tag{6}$$

$$0 \le P^{dis}(t,s) \le 0.5 \times E_{bat} \times u^{dis}(t,s) \tag{7}$$

$$u^{ch}(t,s) + u^{dis}(t,s) \le 1 \tag{8}$$

$$SOC(t,s) = SOC(t-1,s) + \frac{\Delta t}{E_{bat}}(P^{ch}(t,s)\times\eta - \frac{P^{dis}(t,s)}{\eta}) \tag{9}$$

$$SOC_{init} = SOC_{fin} = SOC_{min} = 10\% \quad ,\forall s \tag{10}$$

$$10\% \le SOC(t,s) \le 100\% \tag{11}$$

$$if \quad \pi(t,s) \ge \pi(t,s') \rightarrow P^{ch}(t,s) \le P^{ch}(t,s') \tag{12}$$

$$if \quad \pi(t,s) \ge \pi(t,s') \rightarrow P^{dis}(t,s) \ge P^{dis}(t,s') \tag{13}$$

Concerning equation (1), the income of a battery storage facility can be increased by frequently charging and discharging; however, the degradation cost of the battery, as shown in the second part of (1), goes up and consequently, the operational life and profit is decreased. That means there is a trade-off between revenue comes from the storage arbitrage and its degradation cost, which is addressed by the optimization. The battery cycle life can be calculated according to the amount of depth of discharge (DOD). According to [18], the DOD can be calculated from (2), considering the energy changing pattern and battery's efficiency. It is proved that the degradation of the battery storage corresponds to its energy changing; hence, in this paper, the formulation is modified in a way that if the battery keeps its operational statue (i.e., charging or discharging) at following time steps, then the amount of DOD will be reduced. Furthermore, there is a linear relationship between DOD and LABS cycle life, which is stated in (3). The coefficients A and B are -4775 and 4955, respectively [19]. Considering the negative amount for A, the lower amount for DOD, the higher battery life cycle. The real battery life as a function of life cycle is also described by (4) and E_{bat} shows the total capacity of the battery storage. Finally, the degradation cost of the battery is calculated by (5) considering the investment cost of the battery

storage, i.e., C_{bat} over its actual lifetime under a particular calculated DOD. The amounts of BSS charging and discharging powers are limited in (6) and (7). Equation (8) assures that simultaneous charging and discharging will not happen anywise. The state-of-charge (SOC) is find out for each time and scenario by exploiting (9) according to the amounts of charging and discharging powers and battery's efficiency for $t \ge 1$, where Δt is equal to one hour. The initial, i.e., $t = 0$, and final SOC, i.e., $t = 24$, of are determined by (10). The amount of SOC is limited by (11). Finally, (12) and (13) derive optimal bidding/offering curves for each time. Concerning two last equations, if the forecasted price for a particular scenario s is more than scenario s', then its corresponding purchased power (i.e., charging) is lower, while sold power (i.e., discharging) is higher and vice versa. By ordering the powers and prices over all scenarios, the descending purchase bids and ascending selling offers for each time have appeared.

B. Risk-constrained problem

The profit of energy arbitrage is very vulnerable and is depending on the energy price fluctuations. Hence, a risk-averse decision-maker is interested in very strong risk management techniques. Instead of risk measures, in this paper we use stochastic dominance constraints for selecting optimum portfolio considering acceptable benchmarks. When, the method of stochastic dominance is applied to a stochastic programming, selecting proper benchmarks is very important, since, the problem runs over these benchmarks and inefficient benchmarks will lead to infeasible solutions. Hence, we consider some benchmarks and compare the expected profits over these benchmarks. Selecting benchmarks is directly affected by decision maker's strategy. The stochastic dominance can be used as first order or second order forms, however, the second method has a convex formulation and is adapted in this paper. Considering the instructions by [20], the risk constrained problem of optimal bidding strategy problem for battery storage have two additional constraints as (14) and (15). $S(s,v)$ is a positive decision variable, which measures the shortfall of the objective function under scenario s below scenario v.

$$k(v)-(\sum_{t}\begin{Bmatrix}P^{dis}(t,s)-P^{ch}(t,s))\times\pi(t,s)\\-C_{\deg}\times(P^{ch}(t,s)+P^{dis}(t,s)\end{Bmatrix})\le S(s,v) \tag{14}$$

$$\sum_{s}\rho(s)\times S(s,v) \le \sum_{v'}\tau(v')\times max(k(v)-k(v'),0) \tag{15}$$

III. NUMERICAL EVOLUTIONS

In this paper, an autonomous LABS with the total energy capacity of 27.19 kWh and the investment cost of 96 $/kWh, i.e., C_{bat} equals to $ 2610.24 [19], is used to participate in the energy arbitrage market. The charging and discharging efficiency is equal to 90%, E_{bat} is equal to the total energy capacity of the LABS, i.e. 27.19 kWh. Considering the small capacity of the LABS, it is assumed that this storage unit is a price-taker and its charging/discharging actions cannot influence the market prices. Hence, the critical factor for the LABS is price forecasting. The market price samples are based on data given by [21]. In order to make a low computational burden, at first, 1000 price scenarios are produced and assumed that the market prices
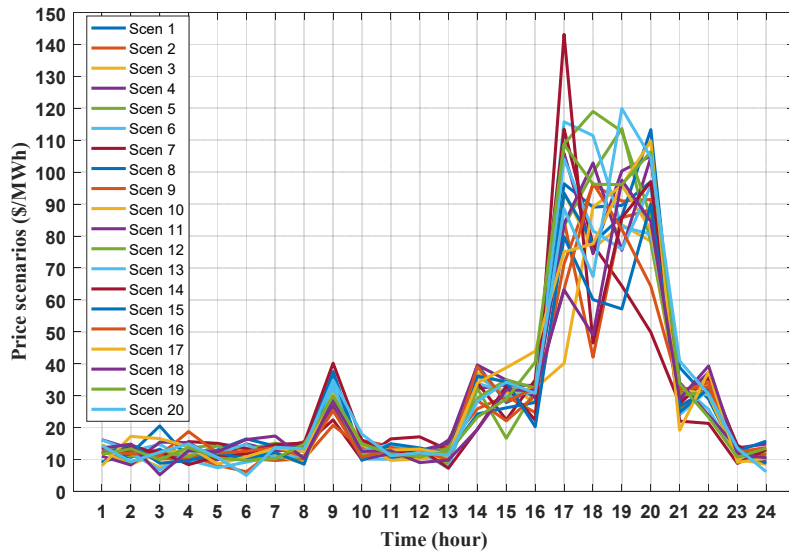
Fig. 1. Price Scenarios

follow normal distribution function, then the produced scenarios reduced to 20 representative scenarios using Kantorovich distances and fast forward selection method. The price scenarios are shown in Fig. 1 and the possibilities of these scenarios are reported in Table I. For risk-constrained problem two benchmarks with four scenarios are considered. The proposed method finds the optimum solutions in a way the profit distribution outperforms these acceptable benchmarks. The benchmarks are shown in Table II. Considering scenarios mentioned above, the presented optimization, including equations (1)-(13), as a risk-neutral problem is modeled as mixed-integer non-linear programming (MINLP) and solved by GAMS optimization software using DICOPT solver. In the following, the results are shown and discussed for the risk-neutral and risk-constrained cases.

TABLE I. SCENARIOS' PROBABILITIES

Scenario No.	Probability	Scenario No.	Probability
1	0.07	11	0.07
2	0.09	12	0.03
3	0.06	13	0.09
4	0.07	14	0.01
5	0.07	15	0.02
6	0.07	16	0.03
7	0.05	17	0.03
8	0.07	18	0.03
9	0.03	19	0.04
10	0.04	20	0.03

TABLE II. VALUE OF BENCHMARKS' PARAMETERS

Scenario No.	Probability	Benchmark #1 ($)	Benchmark #2 ($)
1	0.25	0	0
2	0.25	0.6	0.3
3	0.25	0.8	0.5
4	0.25	1.2	0.9

As it was mentioned before, the proposed optimization leads to deriving optimal bids and offers should be submitted to the stepwise energy market. The obtained bids should be descending, and the offers should be ascending price- quantity curves. The main advantage of the formulation is that it can generate bid/offer curves without requiring iteration-based methods. The bid curves show purchasing powers, and offer curves show selling powers. Depending on the scenarios, the LABS may or may not submit a bid or offer at a particular time. Nevertheless, in this paper, it is decided to show only three bid/offer curves (i.e., six hours a day) to confirm the validity of the proposed optimization. However, for other hours the LABS may submit a bid/offer with a single step or refuse to participate in the market. As an example, Fig. 2 shows the bidding curves for h=3 in red color, which are descending curves as were expected while the offering curves for h=19 are in blue color, which are ascending curves. The dashed lines are the solutions found by solving the risk-neutral problem, and the bold lines represent the price-quantity bids/offers for the risk-averse strategy. It should be noted that from hour to hour, the bidding and offering curves change meaningfully. Although, a general tendency cannot be imagined for increment or reduction of number of either bidding or offering blocks but the amount of traded powers is reduced when the risk-averse strategy is taken; i.e. the charged/discharged powers by the LABS have been decreased while the price biding/offering ranges are unchanged. Since, the price scenarios are predetermined and the LABS is a price-taker participant, the SOSD method adjusts the powers submitted by the LABS. In fact, the task of SOSD is to restrict the feasible region of the optimization problem to exclude the undesired solutions to make the decisions more conservative regarding the undesired realizations of scenarios.

These bidding/offering curves provide valuable information for the LABS owner to make optimal decisions in the stepwise energy market environment. The obtained results show that according to BSS size and by considering degradation cost, the profit of the assumed battery is around $ 0.7 per day and is decreased by 63% in comparison with a case without considering degradation cost, i.e., $ 1.9 per day. It is worth

mentioning that the obtained results are sharply sensitive to market price scenarios and degradation cost modeling parameters, i.e., A and B, moreover, energy arbitrage is profitable for BSS, only when there is a significant gap between off-peak and peak time prices, so that the incomes cover the investment costs. Otherwise, the participation of the BSS in only energy arbitrage markets might be not recommended because of its degradation cost. The profit per scenario (PPS) for three case studies (risk-neutral (PPS1), benchmark #1 (PPS2) & #2 (PPS3)) are reported in Table III. Moreover, the last row shows the expected profit of each case. For this particular problem with considering scenarios, applying SOSD method in benchmarks 1 and 2 have reduced expected profit more than 50%.

TABLE III.   PROFIT PER SCENARIO

| Scen.	PPS1	PPS 2	PPS 3	Scen.	PPS 1	PPS 2	PPS 3
1	0.646	0.157	0.229	11	1.025	0.291	0.302
2	0.818	0.131	0.193	12	0.970	0.900	0.362
3	0.112	0.810	0.120	13	0.512	0.349	0.302
4	0.766	0.385	0.150	14	1.229	0.688	0.576
5	0.867	0.534	0.119	15	0.419	0.118	0.009
6	1.070	0.869	0.364	16	0.323	0.113	0.00
7	0.502	0.338	0.460	17	0.834	0.188	0.430
8	0.834	0.293	0.288	18	0.306	0.00	0.00
9	0.368	0.127	0.380	19	0.937	0.505	0.441
10	0.524	0.00	0.123	20	1.218	0.460	0.499
Expected profit with risk neutral problem ($)					0.716		
Expected profit with benchmark 1 ($)					0.325		
Expected profit with benchmark 2 ($)					0.213		
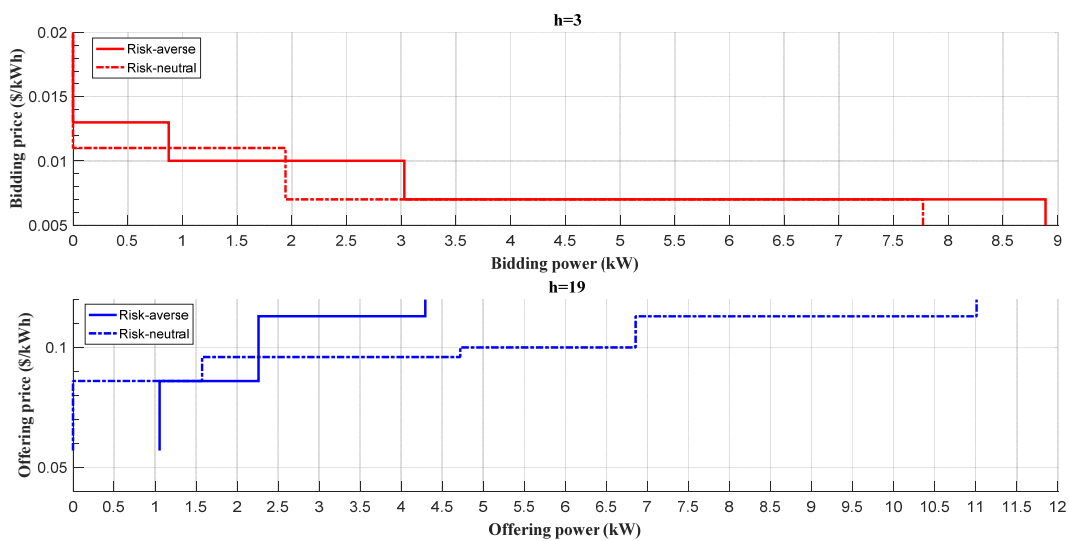
Fig. 2. Optimal price-quantity bids/offers under risk-neutral and risk-constrained strategies
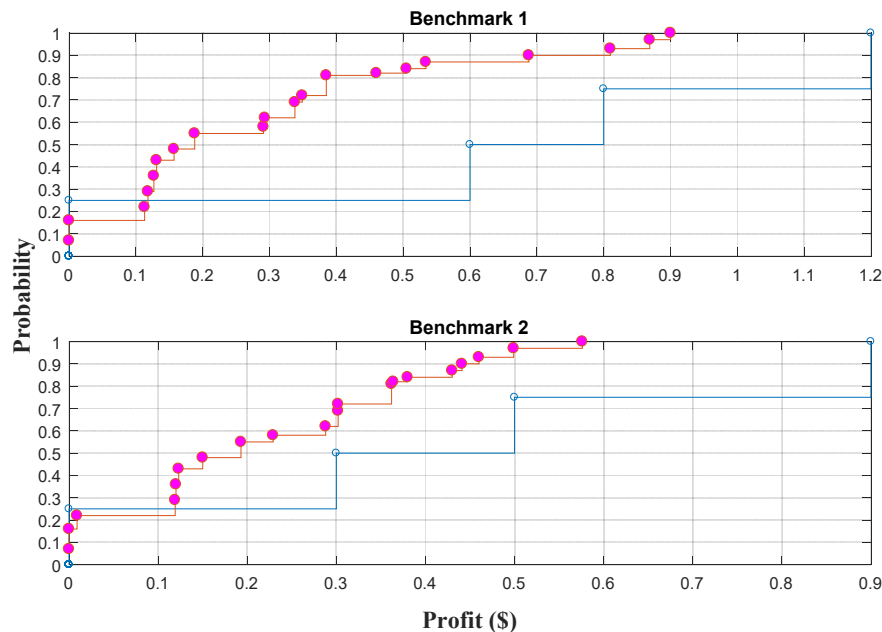

Fig. 3. The cumulative distribution functions for benchmarks 1 and 2

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In Fig. 3, the cumulative distribution function (CDF) of profit considering benchmarks 1 and 2 has been plotted. As can be seen, as the bidding/offering strategy is changed to risk-averse, the curves submitted to the market is altered. From Fig. 3, the CDF of the arbitrage profit under the proposed risk-constrained problem dominates the CDF of both benchmarks #1 and #2 in the sense of SOSD and would be chosen by a risk-averse decision-maker. Moreover, the benchmark #2 is more restrictive than benchmark #1 as it was shown before in Table III. As can be seen, for a particular probability in both benchmarks #1 and #2, the gained profit is lower than the profit of benchmarks and is more conservative.

IV. CONCLUSION

Intuitively, battery storages that are used widely in smart homes and electric vehicles have great potential to participate in arbitrage markets. The frequent charge and discharge cycling of battery storage incurs faster depreciation and causes economic harms. In this paper, without loss of generality, optimal participation of lead-acid battery systems in stepwise energy markets has been investigated. The degradation cost of the lead-acid battery system integrated into the objective function of the proposed optimization. Also, stochastic programming is used to model the uncertainty of the market price via price scenarios. The stepwise bidding/offering curves that should be submitted to the energy market are developed. The obtained results show that consideration of the degradation model of the lead-acid battery decreases the obtained profit by about 60% in a short-term run. Furthermore, a risk management technique, named second order stochastic dominance constraints are added to risk neutral problem. Two acceptable benchmarks are considered, and optimal bidding curves are developed. The expected profit for risk neutral, benchmark 1 and 2 are compared. Considering benchmarks, the expected profit is reduced meaningfully. While looking at bidding and offering curves shows that the benchmark 2 leads to a more conservatism condition compared to risk neutral case, and the traded energy is reduced significantly, however, price bidding is more or less the same. The proposed optimization is general; hence, it can be used for any other BSS technology.

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