Risk Constrained Scheduling of Energy Storage for Load Serving Entities Considering Load and LMP Uncertainties

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Abstract: With the substantial technique development, energy storage (ES) is becoming a promising resource to improve the flexibility and reliability of power system operation. Consequently, ES is obtaining increasing attention from both academia and industry. Due to the increasing fluctuation of locational marginal prices (LMP) as a result of the high penetration of variable wind generation, obtaining the deterministic scheduling decision for ES, i.e., charging/discharging, becomes more complex for load serving entities (LSEs). To address this challenge, a risk constrained scheduling model is proposed in which the objective is to maximize the LSE's profit by optimially scheduling ES charging/discharging profile and considering the possible financial loss risk. Conditional value at risk (CVaR) term has been included in the objective function to negate the risk of associating the uncertainties from forecasting the market price and load. Numerical examples verify the proposed method in ES scheduling considering risk.

Keywords: Conditional value at risk (CVaR), energy storage, electricity market, load serving entity (LSE), risk aversion.

1. INTRODUCTION

Energy storage (ES) has obtained increased attention from both academia and industry due to the large amount of variable renewables and smart grid technologies in power system. Planning and operating the power grid towards a more flexible, reliable and environmentally friendly system has been the task of many energy policy makers and researchers from ISOs, Utilities and Regulators. In the United States, energy provided from wind power should increase to 20% by the end of 2030 as demonstrated by a task introduced in [1]. Consequently, ISO managed markets accommodate significant wind percentage growth in terms of the generation portfolio capacity.

Facilitating ES to increase power system operational flexibility is commonly regarded as a logical measurement for systems accommodating large amounts of renewable energy. California Public Utility Commission (CPUC) has established rules that require all the utilities to procure more than 1,300 MW of energy storage by 2020, i.e., roughly 3%~4% of CAISO's summer peak load [2]. Therefore, investigating the benefit and potential impact of ES integration into the grid has obtained increasingly urgent attention from both regulators and policy makers. From the LSEs' viewpoint, as their ES procurement becomes inevitable as well as growing larger in scale in the near future, LSEs should better understand how to optimally schedule ES under the condition of high penetration of wind power in order to either increase investment returns or reduce ratepayer's cost.

Previously, there have been some research works concerning the optimization of ES in the literature. In [3], ES is utilized by wind generation in the deregulated electricity market to maximize its own profit through mitigating its power fluctuation. In [4], Discrete Fourier Transform (DFT) approach is proposed to optimize the sizing of ES in a micro-grid. The impact and benefit of ES in the Netherlands' electricity supply integrating large-scale wind power is investigated from the system and market operators' viewpoints in [5]. ES investment in transmission networks considering the system uncertainties is proposed in [6] based on a robust optimization model. The charging portfolio optimization for plug-in electric vehicles (PEVs), another form of ES which has an increasing penetration, is proposed in [7]. In the near future, the LSEs or the utilities may also play an important role in facilitating the utility-scale ES in their power procurement optimization.

Renewable energy in the market increase the price volatility substantially [8] and taking the coming new devices such as plug-in vehicles, private owned roof photovoltaic (PV) generation [9] and demand response technique [10] into account, the electricity demand fluctuation will also increase [11]. Consequently, to determine the optimal ES charging/discharging portfolio in the DA market requires a large amount of scenarios to represent the price and demand uncertainty. Although the expected profit maximization utilizing stochastic programming has been widely performed to incorporate the scenario set, the financial loss risk is not included in the traditional expected value maximization approach. This means the market participants have the probability to obtain a very low profit return under the extreme scenarios.

Value at risk (VaR) has been utilized as a risk aversion measurement and been incorporated into the optimization model [12]. While VaR method is insensitive to extreme risks, the discontinuous distribution of VaR may lead to failures in optimization problems [13]. Many investors who lost significant amounts of money in the global financial crisis trace their failure to an improper understanding and utilization of VaR. A number of investors have since adopted a related risk measure, conditional value at risk (CVaR) [14, 15]. Therefore, in this paper, CVaR is utilized to quantify the risk potential and integrate the inherent risk management problem into the scheduling strategy including price and load uncertainty.

The rest of this paper is organized as follows: Section 2 introduce the LMP and load forecast method. Section 3 proposes the risk constrained ES scheduling model in which CVaR is utilized to reduce the possible profit risk due to the price and load uncertainty. Section 4 demonstrates the simulation results and numerical analysis to clearly verify the proposed method. Section 5 presents the concluding remarks and points out some future work.

2. LMP AND LOAD FORECAST

In the electricity market, LSEs face the problem of imperfect information, and effectively forecasting the day-ahead (DA) LMPs and regional load is crucial for its ES scheduling. Specifically, load forecast may affect the base-load level and the LMPs forecast may affect the sensitivity of ES hourly charging/discharging scheduling. Forecasting with time series method such as ARMA, ARCH and GARCH models have been applied to forecasts in power systems, and are proven to be effective [16, 17]is an applicable econometric approach for LMP and load forecast which is able to reveal the time-varying trend of the variables compared to the probability methods. In this paper, the Generalized Autoregressive Conditional Heteroskedasticity in mean (GARCH-M) model is introduced for DA electricity load and LMP forecast. Applications of GARCH in mean type models, including the GARCH-M, in power system forecasting are first presented in [17].

Applying the GARCH-M methods to forecast the load and LMPs are shown in Fig.1 and Fig. 2.

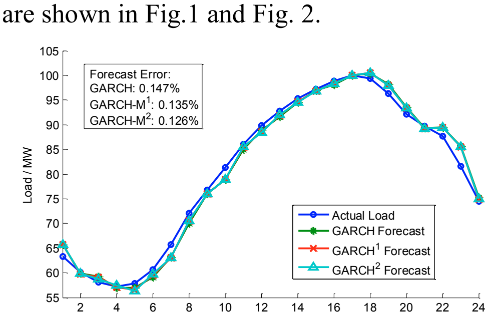

Fig. 1. Load forecast results for June 19 from GARCH models

Regardless of the GARCH model type, there is a forecast error for LMP. Therefore, utilizing one scenario of the forecasting results will lead to high risk for ES scheduling. Consequently, a scenario-based approach is adopted for load and LMP forecast in ES scheduling, where multiple scenarios are generated using forecast outputs from historical data from different period span. The scenarios are shown in Section 4 as case study data inputs.

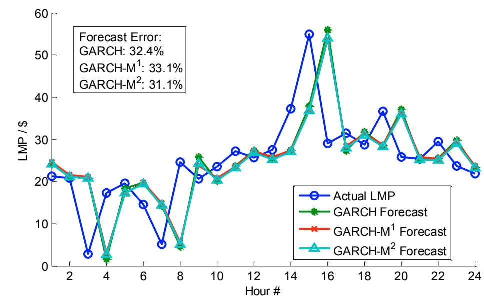

Fig. 2. LMP forecast results for June 19 from GARCH models

3. RISK CONSTRAINED ES SCHEDULING FOR LSE

Fig. 3 shows the diagram of the information and power flow for ES scheduling in DA market in which bids and offers are submitted to the system Independent System Operators (ISOs) [18].

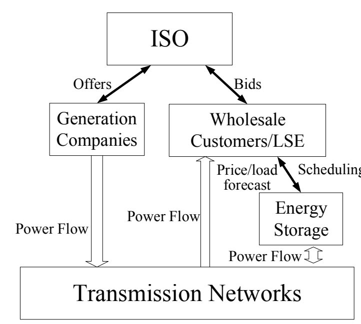

Fig.3. Day-ahead wholesale market structure

In this paper, the LSE is assumed to perform as a price taker and the uncertainty of the market price and load are represented by a set of forecasted scenarios utilizing the forecast method presented in the previous section.

3.1 Net Revenue of Load Serving Entities

The LSE receives a gross revenue from each hour, t, at bus i, given by the product of retail price $\eta_{i,t}$ and the electricity consumption $D^0_{i,t}$. Then, the payment (i.e., the product of spot price $\pi_{i,t}$ and the electricity bid $D_{i,t}$) is subtracted since the LSE pays this amount to the ISO/regional system operator (RTO) in the wholesale market for purchasing electricity at volatile nodal prices ($\pi_{i,t}$). Therefore, the net revenue of a LSE is in (1),

$$R = \sum_{t=1}^{24}\left[\sum_{i\in A}\left(\eta_{i,t}\cdot D^0_{i,t} - \pi_{i,t}\cdot D_{i,t}\right)\right] \tag{1}$$

If the LSE installs some energy storage (ES) system on some of its buses, and assumes that the discharging power of energy storage is positive whereas the charging power is negative, the demand bids on energy storage buses can be expressed as (2),

$$D_{i,t} = D^0_{i,t} - S_{i,t}, \forall i \in SC \tag{2}$$

where Di,t0 is the forecast demand on the buses of LSE bidder; Di,t is the demand that the LSE bids in ISO's Day ahead market. The LSE has some energy storage systems installed on some buses as shown in Fig. 4 (Set SC identifies the buses equipped with ES).

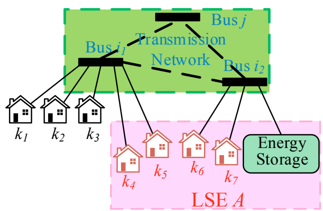

Fig.4. Structure of the LSE with energy storage system

Therefore, the total revenue of a LSE with energy storage can be expressed as follows,

$$R = \sum_{t=1}^{24} \left[\sum_{i \in A} (\eta_{i,t} - \pi_{i,t}) \times D^0_{i,t} + \sum_{i \in SC} \pi_{i,t} \times S_{i,t} \right] \tag{3}$$

This model is a general model for an LSE utilizing energy storage in the day ahead market. Note that in Eq. (1) and (3), the demand ($D^0_{i,t}$) and price ($\pi_{i,t}$) are the forecasted values and the uncertainty of their forecasts is represented by a set of scenarios.

3.2 Conditional Value at Risk (CVaR)

CVaR is an extension of VaR that gives the total amount of profit given a confidence level. CVaR is calculated as a portfolio's probability weighted average profit expected in lower than VaR [19]. The relationship between VaR and CVaR is illustrated in Fig. 5 in which CVaR is the expected profit value of the area on the left of VaR. Note that the area on the left of VaR represents the profit that is lower than VaR. Cumulative probability in this area is equal to 1-α. Cumulative probability on the right side (larger than VaR) is equal to the confidence level α. Here α is the confidence level, and usually it is chosen as 95%.

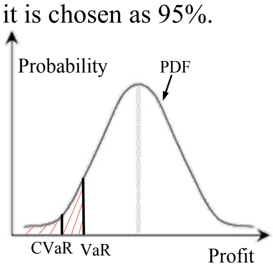

Fig.5. Illustration of CVaR and VaR

Mathematically, the relationship of CVaR and VaR in Fig. 5, can be expressed as,

$$VaR_\alpha(X) = \min\{z \mid F_X(z) \ge 1-\alpha\} \tag{4}$$

$$CVaR_\alpha(X) = \int_{-\infty}^{+\infty} z dF^\alpha_X(z) \tag{5}$$

and
$$F^\alpha_X(z) = \begin{cases} 0 & z > VaR_\alpha(X) \\ \dfrac{F_X(z) - \alpha}{1-\alpha} & z \le VaR_\alpha(X) \end{cases} \tag{6}$$

where X is a random variable (profit or net revenue); z in (9) to (11) is the profit value; α is the confidence level within [0, 1]; F_X is the cumulative probability function [20].

3.3 Risk Constrained Scheduling of Energy Storage System

The daily scheduling of energy storage system [21-23] is based on the daily forecasted demand and LMP. In Eq. (1) to (3), $D^0_{i,t}$ and $\pi_{i,t}$ are forecasted. To model the uncertainties of associating the forecast load and LMP, a set of probabilistic scenarios are generated for load and LMP forecasting, respectively. For the risk aversion purpose, CVaR is included in the objective function. The model for risk constrained energy storage scheduling in this situation is in (7)-(17). In the scheduling process, the decision variables are the 24 hours ES charging/discharging power output schedule. In the objective function (7), CVaR has already been integrated and β from 0 to 1 is the risk aversion parameter to model the tradeoff between the expected profit and financial loss risk. The higher β value signifies a higher risk aversion level, meaning that the result will be more conservative. The analysis of β on ES scheduling optimization results will be studied in Subsection IV.B

$$\text{Maximize } (1-\beta)\sum_{\omega,\xi} p_\omega \cdot p_\xi \cdot R_{\omega,\xi} + \beta \cdot CVaR \tag{7}$$

$$\text{s.t. } R_{\omega,\xi} = \sum_{t=1}^{24} \left[\sum_{i \in A} (\eta_{i,t} - \pi_{\omega,i,t}) \cdot D^0_{\xi,i,t} + \sum_{i \in SC} \pi_{\omega,i,t} \cdot S_{i,t} \right] \tag{8}$$

$$CVaR = VaR - \frac{1}{1-\alpha} \sum_{\omega,\xi} p_\omega \cdot p_\xi \cdot \delta_{\omega,\xi} \tag{9}$$

$$VaR - R_{\omega,\xi} \le \delta_{\omega,\xi} \tag{10}$$

$$\delta_{\omega,\xi} \ge 0 \tag{11}$$

$$D_{i,t} = D^0_{i,t} - S_{i,t}, \forall i \in SC \tag{12}$$

$$S_{i,t} = P^d_{si,t} - P^c_{si,t} \tag{13}$$

$$(E_i^{\min} - E_{i0}) \le \sum_{\tau=1}^{t} (\varsigma_c P^c_{si,\tau} - \frac{1}{\varsigma_d} P^d_{si,\tau}) \le (E_i^{\max} - E_{i0}), \quad i \in SC, \quad t = 1, \dots, 24 \tag{14}$$

$$0 \le P^c_{si,t} \le P^{c(\max)}_{si} \chi^c_{i,t} \tag{15}$$

$$0 \le P^d_{si,t} \le P^{d(\max)}_{si} \chi^d_{i,t} \tag{16}$$

$$\chi^c_{i,t} + \chi^d_{i,t} \le 1 \tag{17}$$

where $CVaR$ in (7) is calculated based on scenario-dependent profit. In (7), (8 and (9), $R_{\omega,\xi}$ is the profit in LMP scenario ω and load scenario ξ; $\delta_{\omega,\xi}$ is the auxiliary variable used for conditional value at risk ($CVaR$) calculation in scenario ω and ξ which is equal to zero if this scenario has a profit larger than VaR and is the difference between the profit of this scenario and VaR if this difference is greater than zero; E_i^{min} and E_i^{max} are the minimum and maximum ES capacity status, respectively, at bus i. $P_{si}^{c(\max)}$ and $P_{si}^{d(\max)}$ are the maximum charging/discharging power of ES devices; Equation (12) is the actual demand at energy storage buses; (13) is the power output of ES (ES's power output is positive for discharging and negative for charging); (14) is the capacity limit of ES system; (15) and (16) are the charging/discharging power output limit and (17) is the charging/discharging status constraint (only one status is active at one time).

4. CAST STUDIES

4.1 Study Case

In this study, the forecast load and LMP curves of the LSE utilizing the forecast method proposed in Section 2 are shown in Fig. 6 and Fig. 7. The electricity flat rate of the LSE is \$30/MWh. The ES parameters are in Table 1. In order to account for the uncertainty around the true outcomes of day-ahead prices and load, CVaR is used to negate the risk associating the ES scheduling. In the CVaR calculation, the confidence level is 80%~99% and the risk aversion is represented by $\beta \in (0,1)$, which will be tabulated to vary within this range and to verify the impact of risk aversion on ES scheduling. Numerical results demonstrate how the proposed ES scheduling approach for LSE increases the expected profit and reduces the related risk.

Table 1. Parameters of Energy Storage System

E^{min}	10%	$\varsigma_d / \varsigma_c$	0.9
E^{max}	90%	$P^{c(max)}$	30%
E_0	20%	$P^{d(max)}$	30%

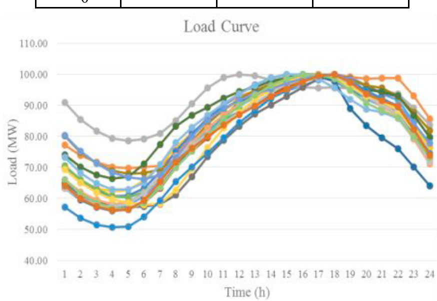

Fig.6. Forecast load under different scenarios

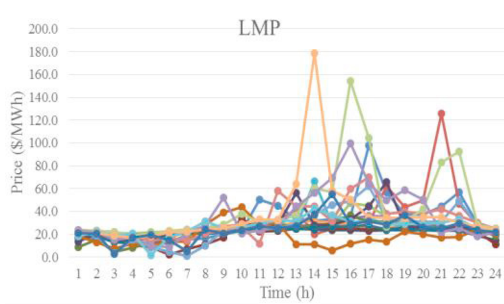

Fig.7. Forecast bus LMP under different scenarios

4.2 Implication of Risk Aversion Level

In this subsection, the impact of different risk aversion levels on ES scheduling will be investigated. In this study, the ES capacity is 50 MWh, the confidence level is 95% and the impact of confidence level and ES capacity on the LSE's profit will be studied in the next subsections.

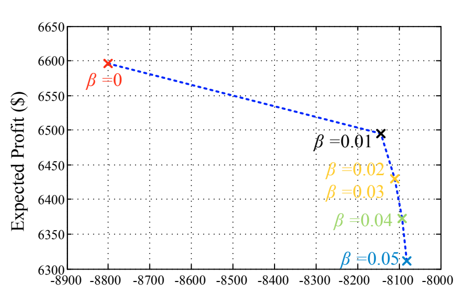

Fig.8. Efficient frontier of LSE's expected profit and its risk

Fig. 8 demonstrates the efficient frontier of LSE's profit and CVaR under different risk aversion levels (β value means the risk aversion level). It is obvious that with a higher risk aversion level, the expected profit is lower. But under this condition, CVaR is higher which means that the LSE's probable expected profit for the lowest 5% increases and therefore the LSE has a lower financial risk.

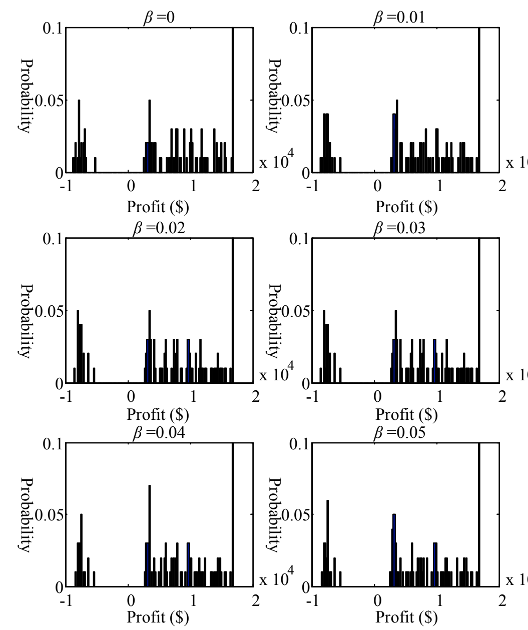

Fig.9. LSE's profit density bar under different risk levels

Fig. 9 shows the probability densities in different β cases. It also demonstrates that high risk aversion level can increase the profit value of the lowest 5% scenarios. From Fig. 9 it also can be concluded that high risk aversion may decrease the probability of higher profit scenarios which leads to the lower expected profit shown in Fig. 8. However, this expected profit reduction is a trade-off of the financial risk aversion to hedge the extreme low profit return.

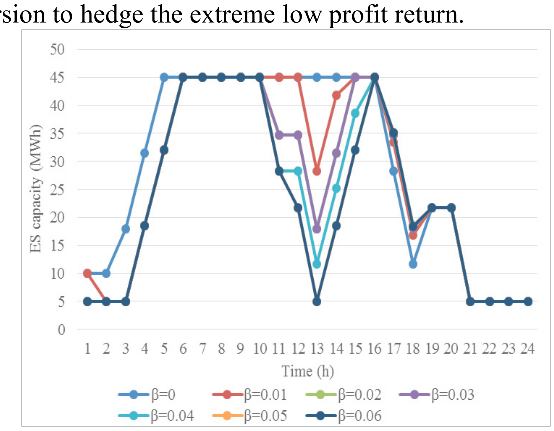

Fig.10. ES scheduling status under different risk aversion levels

Fig. 10 shows ES capacity status scheduling results under different risk aversion cases. It demonstrates that the risk level changes the ES day-ahead scheduling significantly especially from 10 am to 19 pm. From the LMP forecast curves in Fig. 8, during this period, the price fluctuation is more volatile and different risk aversion levels will lead to different ES scheduling. Therefore, considering the price and load uncertainty in the LSE's ES scheduling, the risk aversion model should be included. Ignoring the financial risk due to the LMP and load uncertainties or choosing an inappropriate risk aversion level can lead to an ES scheduling decision that will have a higher financial loss.

4.3 Implication of Confidence Level

This subsection will study the influence of the confidence level (α value) in the optimization model. The risk aversion level is fixed with β=0.05 and ES capacity is also 50 MWh. Table 2 is the expected profit results, CVaR and VaR value under different α value. Fig. 11 is the probability density figures in different α cases. ES scheduling results under various α are shown in Fig. 12.

From Table 2, although CVaR and VaR increase when α decreases, the probability of profit lower than this VaR value increases because the confidence level reduces. Consequently, comparing the risk aversion results under different confidence levels is useless. A higher CVaR under a lower confidence level does not mean the risk of profit loss is lower. Therefore, in the LSE's risk constrained ES scheduling, a reasonable confidence level should be pre-determined. Fig. 12 and Fig. 13 demonstrate that the confidence level also can change the profit density profile. With a higher confidence level, the optimization process will try to increase the profit for more scenarios, although this may lead to a reduction in the expected profits. Consequently, the profit risk decreases because the probability of lowest profit scenarios decreases and the scenarios with medium profit increases.

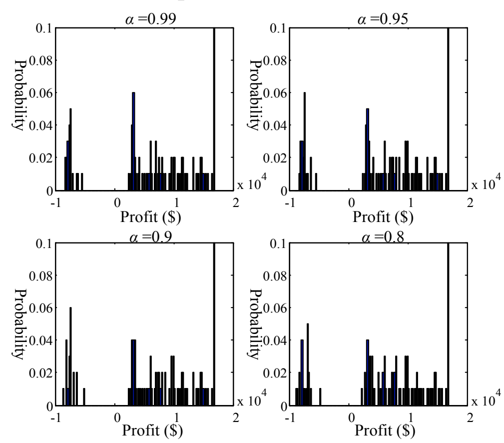

Fig.11. LSE's profit density bar under different confidence levels

Table 2. Expected profit, CVaR and VaR Results under different Confidence levels

α	Exp. Profit ($)	CVaR	VaR
0.99	6296.601	-8282.84	-8282.84
0.95	6311.924	-8080.65	-7905.03
0.9	6315.134	-7935.53	-7403.51
0.8	6382.319	-7272.69	2347.47

Fig. 12 shows the ES scheduling results under different confidence levels (α value). From this figure, it is demonstrated that that the confidence level has the impact on ES scheduling. But compared with Fig. 9, it can be concluded that the risk aversion level (β value) has a more obvious impact on ES scheduling than do the confidence levels (α value). In this study, it is also demonstrated that ES scheduling results don't change significantly when the confidence level is higher than 90%. And from Table 2, the financial risk represented by CVaR does not obviously decrease from -7935.53 to -8282.84 by increasing the confidential level from 90% to 99%. Therefore, in the practical application, 95% as the confidence level is good enough for the ES scheduling optimization purpose.

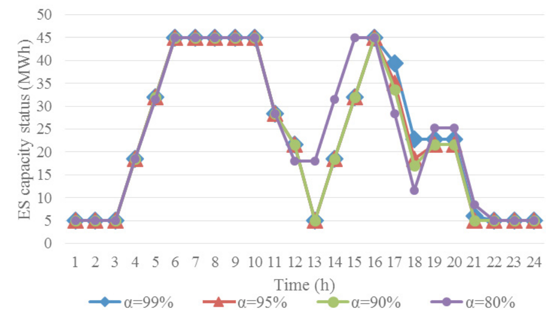

Fig.12. ES scheduling status under different confidence levels

4.4 Impact of ES Capacity

Fig. 13 is Expected profit, CVaR and VaR curves under different ES capacities. The primary y axis on the left is for profit value and the secondary y axis on the right is for CVaR and VaR value. In this study, the risk aversion β=0.05 and the confidence level α=95%. Fig. 13 shows that the expected profit, CVaR and VaR all increase with ES capacities. This means that both the expected profit and the financial risk of the profit can be reduced by increasing ES capacity.

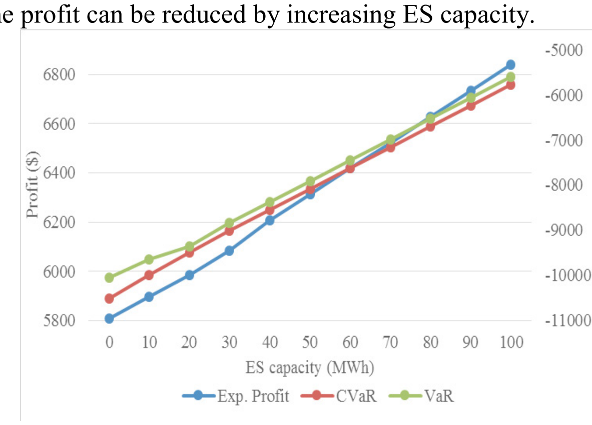

Fig.13. LSE's expected profit, CVaR and VaR

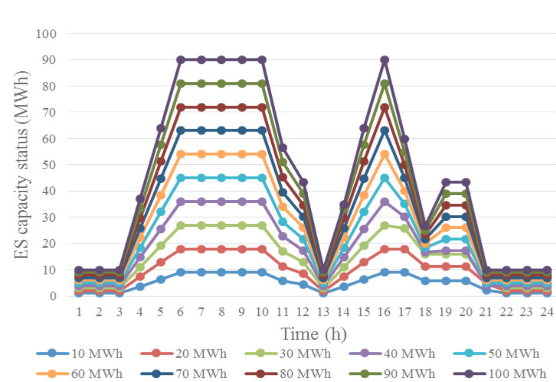

Fig.14. ES scheduling under various ES capacity

Fig. 14 is the ES scheduling status under different ES capacities. Obviously, ES charging/discharging pattern portfolio does not change much with respect to ES capacity. Note that in this study, the LSE performs as a price taker in the market and its ability to bid and change LMP will be investigated in future work. In this paper, the uncertainty of LMP is represented by a set of forecasted LMP curves shown in Fig. 7 obtained through the LMP forecast approach in Section 2.

5. CONCLUSIONS

In this paper, a risk constrained ES scheduling method for the LSE is proposed in which the uncertainty of demand and price are considered. The main contribution of this work can be summarized as follows:

1) Conditional value at risk (CVaR) is utilized as the risk aversion measure in ES scheduling optimization model which is formulated as a mixed-integer linear programming (MILP) problem and solved by available software;
2) The simulation results demonstrate that considering the risk in ES scheduling model can significantly change the ES charging/discharging portfolio results and the LSE's expected profit.
3) Risk aversion level and confidence level in the optimization model for the price and load uncertainty are another factors that can impact ES scheduling results. Through the choice of these parameters, the trade-off between the expected profit and financial risk is made.
4) Although the LSE's expected profit and financial risk increase with ES capacity, the ES capacity is not among the factors that can change the scheduling portfolio of ES.

Future work includes the DA market clearing that includes LSE's bids considering ES which takes into account the ES's capability to change DA LMP results.

6. ACKNOWLEDGEMENT

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