Multipurpose Strategy for Energy Storage System Based on Capital Asset Pricing Model With Ensemble Approach

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Multipurpose strategy for energy storage system based on capital asset pricing model with ensemble approach

KAZUFUMI YUASA[1, 2], Member, IEEE, MIKI UESHIMA[2], TADATOSHI BABASAKI[2], Member, IEEE, and ICHIRO OMURA[1], Member, IEEE

[1]Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Fukuoka, 808-0196 Japan

[2]Service Development Division, NTT FACILITIES, INC., Tokyo, 108-0023 Japan

Corresponding author: Kazufumi Yuasa (yuasak23@ntt-f.co.jp).

ABSTRACT In this paper, we present a multipurpose operation strategy for the efficient distribution of power to multiple power services from a single battery energy storage system (BESS). The proposed operation strategy uses a modern portfolio theory of financial engineering known as the capital asset pricing model to determine the allocation of BESS discharge power. Using this strategy, it is possible to quantitatively evaluate the expected return and risk in BESS operation and achieve the maximum expected return for the selected acceptable risk. Further, the predictability of the expected return is improved by applying the ensemble approach to the estimation model of the expected return. A one-year long performance test was conducted at the Japan Electric Power Exchange using the proposed operation strategy. A mean absolute error of approximately 2.0% between the expected return of the proposed strategy and the actual return was obtained, confirming the accuracy of the proposed strategy.

INDEX TERMS Batteries, Operations and management, Portfolios, CAPM, and Ensemble approach.

I. INTRODUCTION

A. Challenges of BESS for energy service provider

Battery energy storage systems (BESSs), such as stationary energy storage systems and electric vehicles, are being used as the main demand side energy resources (DSRs). In behind-the-meter systems, DSRs are used to reduce the power cost by peak shaving and demand response or as backup in the event of a power outage [1]. In front-of-meter systems, they are used to adjust the supply and demand balance and the frequency or voltage, i.e., to stabilize the system [2]. BESSs are expected to find wider areas of application in the future.

Given the output stability and ease of output control of BESSs, businesses that operate DSRs and provide electric power services (hereinafter referred to as energy service providers) are expected to flourish. However, currently, BESSs are still expensive, and the improvement of their operational economic efficiency is one of the challenges faced by energy service providers.

B. Previous study of operational strategies

Several operational strategies have been proposed to improve the economic efficiency of BESSs. Yang et al. provided simulation results of the optimal installed capacity and break-even point when a BESS is used to regulate the distribution voltage and peak shaving under conditions of photovoltaic power [3]. Ran et al. suggested the classification of consumers according to their load demand and proposed an optimization strategy for electricity charges that considers consumer satisfaction and robustness of control [4]. Sun et al. proposed an economic operation strategy of BESSs based on the use of reusable storage batteries with various states of health [5]. Mahmud et al. proposed an operation strategy for peak shaving that involves charging and discharging groups of electric vehicles based on the prediction of the consumer's power generation and demand [6]. Zhao et al. proposed an economic optimization strategy that considers the loss models' battery life and solar panel together with the time of use [7]. These previous studies mentioned above proposed operation strategies that control the operation pattern of BESSs based on the type of electricity charges and the predicted trading price for a single power service. However, the use of BESS for a single power service is not sufficient for improving economic efficiency because the trading price of a service directly affects the economic efficiency. Therefore, several operational strategies that used a single energy resource for multiple services has also been proposed.

Kazemi et al. proposed a long-term strategy that considers battery life when participating in the frequency regulation and energy markets, simultaneously [8]. Kazemi et al. also proposed a risk-based approach for evaluating the participation strategy of a battery storage system in multiple markets such as day-ahead energy, spinning reserve, and regulation markets [9]. The proposed risk-based model is a max-min problem, which is converted to its equivalent ordinary maximization problem using duality theory. Kazempour et al. proposed the self-scheduling problem of hydro generating company for maximizing the profit of company through participating in the day-ahead energy and ancillary service markets by using a mixed integer non-linear problem (MINP) problem [10]. And, Kazempour et al. also proposed the method to determine optimal storage portfolio from a risk averse perspective by using a tri-level stochastic optimization problem [11]. Mortaz proposed the method to determine interactions among services for distributed energy storage plants, including energy arbitrage, peak demand shaving and various balancing services, and assesses the impact that such interactions have on storage plant remunerability in a multiple service [12]. Nasrolahpour et al. developed a decision-making tool for an energy storage system to determine the most beneficial trading actions in pool-based markets, including day-ahead and balancing market. The proposed model captures the interactions of different markets and their impacts on the functioning of the storage system [13]. Opathella et al. proposed a liner profit-maximizing formulation for grid-connected merchant-owned energy storage systems operating with multiple ancillary services. Their proposed model allows for analyzing and optimizing all ancillary services and energy arbitrage from the energy storage system at the same time, while optimizing the short-term and long-term costs [14]. Rahimiyan et al. proposed an energy management system that controls a cluster of price-responsive demand by using a two-stage procedure (the day-ahead market and the real-time market) based on robust optimization [15]. Zou et al. proposed a multi-period Nash-Cournot equilibrium model for joint energy and ancillary service markets to evaluate the contribution of the ESSs for supporting renewable generation. This model can transform the bi-level equilibrium model into an integrated single-level optimization problem to enhance the computation efficiency [16]. Chaudhari et al. proposed a hybrid optimization algorithm for energy storage management, which shifts its mode of operation between the deterministic and rule-based approaches depending on the electricity price based allocation, and it is calculating capital cost of energy storage and relating it to discharge power [17].

When a single BESS is used for multiple services, it is important to model the long-term expected returns and risks and improve their predictive performance, since the transaction period varies depending on the combined services. The aforementioned previous studies include optimization of revenues and costs, analysis of the correlation between the revenues of each service, and allocation planning when multiple services are used. However, operational strategies that focus on modeling the long-term expected returns and risks of combining multiple services and improving their predictive performance from limited historical data have not been sufficiently studied.

C. Contributions of our study

In this paper, we proposed a multipurpose operation strategy whereby an energy service provider supplies its own single BESS to multiple power services and receives companion. In this proposed strategy, we applied the two important technics to solve the above-mentioned issues. One of them is a modern portfolio theory of financial engineering known as the capital asset pricing model to determine the allocation of BESS discharge power. It is possible to quantitatively evaluate the expected return and risk in BESS operation and achieve the maximum expected return for the selected acceptable risk. Other is the ensemble method, known as bagging (Bootstrap AGGregatING -- Bagging), in order to enhance the predictability of the estimation model in the multipurpose operation strategy. One of the major factors that affect the predictability of an estimation model is the limited number of samples in the dataset used for modeling. Therefore, we considered to apply an ensemble approach to proposed strategy to improve the predictability of the expected rate of return from small dataset.

The contributions of proposed strategy are summarized as follows:

(1) It is possible to quantitatively evaluate the expected return and risk in BESS operation and achieve the expected return for the selected acceptable risk by using CAPM.
(2) It is possible to improve the predictability of the expected return from small dataset by using the ensemble method.

The rest of our paper is organized as follows. We first explain the details of proposed multiple operation strategy in Section II. Then, we present numerical analysis and conditions in Section III. Next, we discuss the results of numerical analysis in Section IV. Finally, we provide our conclusion in Section V.

II. Multipurpose strategy

A. Multipurpose operation strategy based on CAPM

Because energy service providers supply and distribute a limited amount of power stored in a single BESS to multiple power services (hereinafter referred to as products), it is necessary to determine an economically efficient power allocation method. Here, if the distributed products include products such as forward contracts that are traded in bulk over a long period of time, it is necessary to determine the power allocation for other products that are traded in the short term simultaneously. Therefore, it is important to estimate the trading price of each product over a long period. However, because the trading price of electricity is influenced by various external factors, such as electricity demand, weather, fuel price, corporate activities, and policies, it is difficult to accurately estimate the electricity trading price of all traded commodities.

Figure 1 shows the multipurpose operation strategy proposed. This strategy uses historical data on electricity trading prices and, based on the well-known CAPM [19], which is one of the modern portfolio theories in financial engineering, estimates the expected yearly return and risk when supplying power to each product and optimizes the portfolio. Furthermore, the concept of asset allocation based on CAPM is extended to the BESS discharge power control to determine the discharge power allocation plan.

CAPM uses the mean-variance analysis method to quantify risk. In this method, the uncertainty of portfolio revenue is characterized by two quantities: the expected value of return and the variance of return. In the proposed multipurpose operation strategy, it is possible to select a portfolio of discharge power allocation with the highest expected return for any acceptable risk in the operation from the derived efficient frontier based on CAPM.

In summary, with the proposed multipurpose operation strategy, the expected return and risk of the discharge power allocation plan of the BESS is quantitatively evaluated in order to achieve risk diversification in service operation, and it is possible to pursue the maximum expected return for the selected acceptable risk.

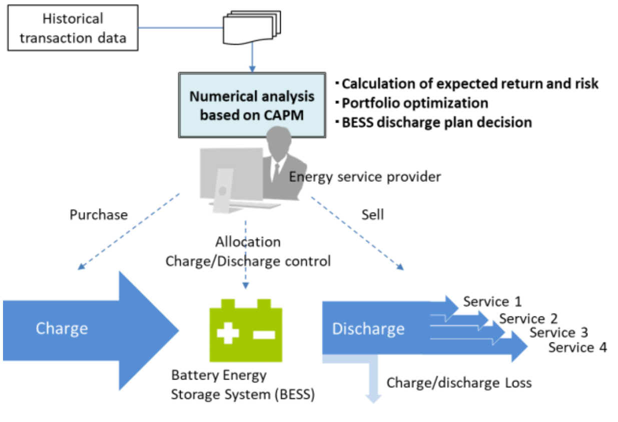

FIGURE 1. Proposed multiple operation strategy

B. Formulation of multipurpose operation strategy

(i) Proposed multipurpose operation strategy

Figure 2 shows a flow chart of the multipurpose operation strategy proposed in this paper. First, the yearly expected return and risk of each product are estimated from the historical data of the electricity trading price (Figure 2 (1)). Next, the expected yearly return and risk of the portfolio combining all products is estimated (Figure 2 (2)). Portfolio refers to the allocation of discharge power by the BESS to multiple products with a predetermined yearly expected return. An efficient frontier is then derived by determining the discharge power allocation that maximizes the expected yearly return for each acceptable risk through optimization (Figure 2 (3)) based on CAPM. Here, the efficient frontier is the solution set of the portfolio in which the combination of risk and expected yearly return is optimal. Finally, these calculated optimized portfolios are averaged into a single charge / discharge portfolio of BESS.

In the Figure2 (4), we used the ensemble method, known as bagging (Bootstrap AGGregatING -- Bagging), in order to enhance the predictability of the estimation model in the multipurpose operation strategy. With the ensemble method, multiple weak learners are trained and used in combination; this method is known to be more accurate than the single learner method [20]. The ensemble method is broadly divided into the sequential ensemble method, in which weak learners are generated sequentially, and the parallel ensemble method, in which they are generated simultaneously. Bagging is a typical algorithm of the latter category, which effectively reduces errors by combining weak learners with low dependence and having randomness incorporated into the learning process.

In bagging, random samples are extracted with replacement from the original data set to generate several

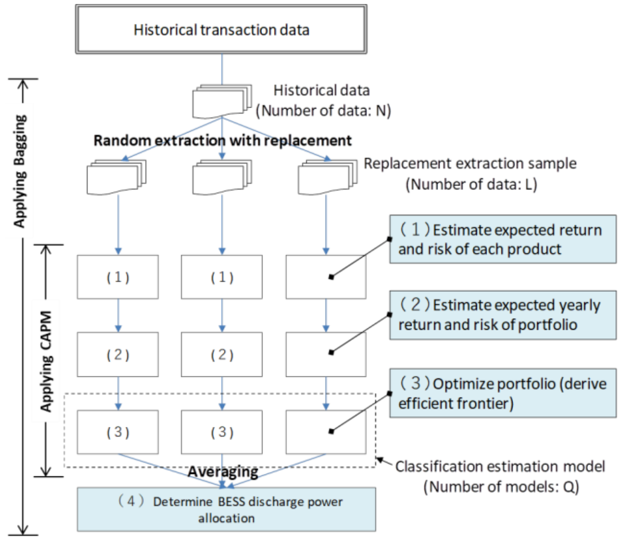

FIGURE 2. Formulation of the proposed multipurpose operation strategy

different data sets with low dependency from a small data set. This removes the constraint on the number of data samples, which affects the predictability, thereby improving the effectiveness of the method. In addition, the algorithm is simple and easy to model, and the calculation time is shortened owing to parallel processing in generally [20]. Thus, in terms of practical use, the constraints on system implementation are very few.

In the multipurpose operation strategy, which applies bagging, Q replaced extraction samples (number of data: L) are generated by random extraction with replacement (random extraction from the original sample allowing duplication) from the historical data of electricity trading price (number of data: N). From this replaced extraction sample, procedures (1) to (3) described earlier are performed to generate Q weak learners (hereinafter referred to as classification estimation model) As a result, each classification estimation derives a different efficient frontier depending on the given replacement extraction sample.

(ii) Expected yearly returns and risk of products

The expected yearly return and risk are estimated from the historical data of the power trading price. Equation 1 shows the daily power procurement unit price C_{ij} ($i = 1,2,3, \ldots, N$) during the charging period of product P_j ($j=1,2,3,\ldots,M$), where N refers to the number of data points (number of days), and M refers to the number of products. For example, C_{11} is the daily power procurement unit price on the first of the N days of product P_1. C_{ij} is obtained by adding the trading fee f_j to the daily power trading unit price T_{ij}. Equation 2 shows the daily power sales unit price B_{ij} of product P_j. For example, B_{11} is the daily power sales unit price on the first of the N days for product P_1. B_{ij} is expressed as the product of $T_{ij} - f_j$ and the power conversion efficiency η of the BESS. This is due to the fact that there is some power loss both at the time of procurement (charging) and at the time of selling (discharging), and the net amount of power that can actually be traded is reduced. The daily return r_{ij} of product P_j is of simple interest with respect to the procurement price and is given by Equation 3. Then, the expected yearly return E (r_j) of product P_j is given by Equation 4 as the simple average value of r_{ij}. Thus, the risk of commodity P_j can be expressed as shown in Equation 5, as the standard deviation σ_j of the daily return. In other words, the uncertainly of the transaction price is reflected in the numerical model as the standard deviation of the daily return rate based on the actual transaction data of the power trading price.

$$C_{ij} = (T_{ij} + f_j) \tag{1}$$

$$B_{ij} = (T_{ij} - f_j)\eta \tag{2}$$

$$r_{ij} = \frac{(B_{ij} - C_{ij})}{C_{ij}} \tag{3}$$

$$\mathrm{E}(r_j) = \frac{\sum_{i=1}^{N} r_{ij}}{N} \tag{4}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{N}\left(r_{ij} - \mathrm{E}(r_j)\right)^2}{N}} \tag{5}$$

(iii) Expected yearly return and portfolio risk

In financial engineering, a portfolio is the collection of assets held by an investor and their composition ratio. In this paper, a portfolio refers to the allocation of the discharge power by a BESS to product P_j, whose expected yearly return is $E\ (r_j)$. The expected yearly return of product P_j can be expressed as the column vector $\boldsymbol{E}\ \boldsymbol{(r)}$ of M products, each of which have expected yearly return of $E\ (r_j)$, as shown in Equation 6. The variance-covariance matrix $\boldsymbol{S}$ of the expected return $E\ (r)$ is an $M \times M$ determinant that depends on the number of products and is given by Equation 7. Equation 8 shows the column vector x_j of the discharge power allocation $\boldsymbol{x}$ for each product. The discharge power allocation is the ratio of the BESS discharge power to each product and takes a value between 0 and 1. The expected return E_p of the portfolio is calculated as the weighted sum of the discharge power allocation x_j and the expected yearly return $E\ (r_j)$ for each product, as shown in Equation 9. The variance of the portfolio σ_p^2 is given by Equation 10, which is obtained from Equations 7 and 8 [21]. Then, the portfolio risk σ_p is given by Eq. 11.

$$\mathbf{E}(\boldsymbol{r}) = \begin{bmatrix} E(r_1) \\ E(r_2) \\ \vdots \\ E(r_M) \end{bmatrix} \tag{6}$$

$$\boldsymbol{S} = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{M1} \\ \vdots & \ddots & \vdots \\ \sigma_{1M} & \cdots & \sigma_{MM} \end{bmatrix} \tag{7}$$

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \end{bmatrix} \tag{8}$$

$$E_p = \sum_{j=1}^{M} x_j E(r_j) \tag{9}$$

$$\sigma_p^2 = \boldsymbol{x}^{\boldsymbol{T}}\boldsymbol{S}\boldsymbol{x} = \sum_{j=1}^{M}\sum_{k=1}^{M} \boldsymbol{x_j x_k \sigma_{jk}} \tag{10}$$

$$\sigma_p = \sqrt{\sum_{j=1}^{M}\sum_{k=1}^{M} \boldsymbol{x_j x_k \sigma_{jk}}} \tag{11}$$

(iv) BESS discharge plan

The solution set plotted using the acceptable risk of the portfolio and the maximum value of the expected yearly return is called the efficient frontier. Portfolios on the efficient frontier are known to be the best combination of

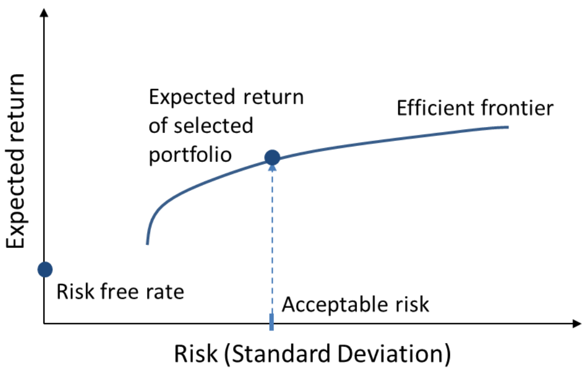

FIGURE 3. Efficient frontier

mean and variance [21]. Figure 3 shows an overview of the efficient frontier. In the proposed multipurpose operation strategy, the portfolio with the expected return of risk allowed by the energy service provider is selected from this efficient frontier; then, the discharge power allocation to each product of the BESS is determined.

To derive an efficient frontier, Equations 12–14 were formulated as an optimization problem aimed at maximizing the expected return for any acceptable risk of the portfolio. Equation 13 expresses the equality constraint that the sum of the allocation x_j for each product in the portfolio must be 1. The acceptable risk of the portfolio is varied, and the maximum value of the expected yearly return for each acceptable risk is calculated by optimization. The Solver function of a spreadsheet software was used for optimization calculation, and the optimization algorithm used was the generalized reduced gradient method, which is used for solving nonlinear programming problems.

$$\text{maximize } E_p = \sum_{j=1}^{M} x_j E(r_j) \tag{12}$$

$$\text{subject to } \sum_{j=1}^{M} x_j = 1 \tag{13}$$

$$0 \leq x_j \leq 1 \ (\text{j}=1,2,3\cdots,\text{M}) \tag{14}$$

In the proposed multipurpose operation strategy shown in Figure 2, the efficient frontier of the classification estimation model is calculated in parallel. Then, in the efficient frontier of each classification estimation model, the discharge power allocation is averaged for all portfolios with the same acceptable risk—this becomes the discharge power allocation rate x_j' of the new portfolio. Assuming that the number of classification estimation models is Q, x_j' is calculated as follows:

$$x_j' = \frac{x_1+x_2+\cdots+x_h}{Q} = \frac{\sum_{h=1}^{Q} x_h}{Q}, \tag{15}$$

Where SOC_{ini} denotes the present value of the charge state of the state of charge, SOC_{min} is the lower limit of operation, and C is the rated capacity. Then, the amount of power W charged in the BESS is given by Equation 16. The control target value w_j of the amount of charge/discharge power by BESS for each product is given by Equation 17, using W and the allocation x_j' of the selected portfolio.

$$\text{W} = (SOC_{ini} - SOC_{min})C \tag{16}$$

$$w_j = x_j'\text{W} \tag{17}$$

III. Numerical analysis

In this study, a multipurpose operation strategy was applied to the day-ahead market, real-time market, and forward market of the Japan Electric Power Exchange [22], for assuming that it would be provide charge / discharge power of BESS to the reserve services because the proposed strategy determines the discharge plan in advance. Table 1 presents details of the markets considered. In the day-ahead market, the electricity for the following day is exchanged (bought and sold). In the real-time market, electricity is traded to deal with the unexpected supply demand mismatch that occurs between the day-ahead market and the actual supply and demand. In the forward

TABLE I
TARGET POWER SERVICE

Item	Day-ahead market	Real-time market	Forward market
Product symbol P_j	P_1~P_{48}	P_{49}~P_{96}	P_{97}
Product classification	48 products divided into 30-minute periods each day		1 product for a specific period
Trading fee f_j (JPY/kWh)	0.030	0.10	0.68
Product properties	Risk product		Risk-free product

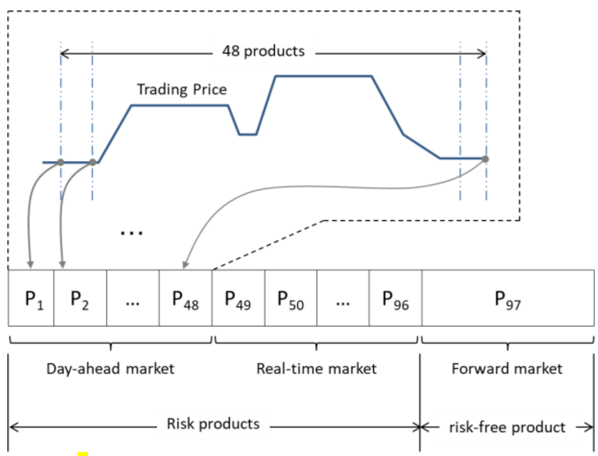

FIGURE 4. Plot of target product

market, medium to long-term electricity is traded at a fixed price. In the forward market, the electricity of constant output is traded as one product during the trading period.

The day-ahead market and real-time market are subject to daily and hourly fluctuations in trading price. In the forward market, the price may be fixed for the trading period. For this reason, the day-ahead and real-time markets are classified as risk products in CAPM, and the forward markets are classified as risk-free products.

Figure 4 shows a plot of the target product group. In each market, electricity may be traded as 48 products, each of which is a 30-minute block of a day. In the forward market, multiple time blocks are treated as one trading product; however, in this paper, they are treated as products that can be traded every 30 min to match the conditions with other products.

In this proposed strategy, as the number of data for the daily return rate shown in Eq.3 increases, the number of data for the variance (risk) of the return rate of the service increases, and the accuracy of the model becomes higher. For this reason, it is preferable to fix the charging block. 48 charging blocks can be selected from 0:00 to 24:00, although the historical data shows that the midnight block is the cheapest in terms of procurement price, so we conducted a case study with a fixed block at 0:00-0:30 in this study. In practical terms, charging of the storage battery (purchase of electricity) will be performed for 30 min during the first of the time blocks (00:00 to 00:30) and the discharge of the battery (sale of electricity) will be performed during the remaining 47 time blocks (00:30 to 24:00). That is, of the 97 products targeted for trading, a total of 95 products including 47 products in the day-ahead market (P_2–P_{48} in Figure 5), 47 products in the real-time market (P_{50}–P_{96} in Figure 5), and one product in the forward market (P_{97} in Figure 5) are trade products that are discharged and supplied by BESSs.

Table 1 also lists the trading fees obtained from Reference [22]. The trading fee in the forward market is a fixed monthly fee, but to unify the conditions with other products, we consider the deemed value of the cost per 30-minute time blocks (1,000 yen/month × 12 months ÷ 365 days ÷ 48 time blocks ≒ 0.68 yen). The BESS charge/discharge efficiency η was set based on the power conversion efficiency of the BESS in the market; the AC-DC and DC-AC power conversion efficiencies were set to 0.9, and the charge/discharge efficiency was set to 0.9 × 0.9 = 0.81. In general, the charge/discharge efficiency of a BESS varies depending on the load factor; however, for simplicity, it was set to a constant value in this study.

Because the main purpose of this study is to confirm the effectiveness of the return risk analysis and forecast performance improvement of operation strategies that apply CAPM and ensemble approach, the specific installed capacity, charge/discharge rate of the storage battery, and transient response were not considered in the proposed model. However, the proposed operation strategy assumes an allocation plan at 30-minute intervals based on transaction times, and we believe that short-time response characteristics and other factors will not have much impact. On the other hand, these factors will affect the accuracy of the results as errors. We are considering improving the accuracy of the prediction model by relearning it with power data to be collected during operation, and to improve the robustness of the prediction model by applying the DFSS method (Design For Six Sigma). The charge/discharge current value corresponding to the amount of power (kWh) charged/discharged in Equation 17 must not be greater than the charge/discharge rate of the storage battery used for the BESS. The return risk is a dimensionless value and can be generalized regardless of the installed capacity.

Historical data for the three years from FY2016 to FY2018 were used for the numerical analysis. Figure 5 shows the changes in trading prices in each market (7-day moving average). It can be seen from the figure that trading prices tend to vary from year to year; hence, it is difficult to estimate the trading price for any year from the data set of the previous year. The expected yearly return and risk of all products for each year were derived using Equations 4 and 5, and the results are shown in Figure 6. The expected yearly returns are between −25.0% and 66.7% in FY2016, between −27.9% and 16.9% in FY2017, and between −33.5% and 13.7% in FY2018. From the figure, it can be seen that the expected returns differ from year to year.

Using these data sets, the estimation models (efficient

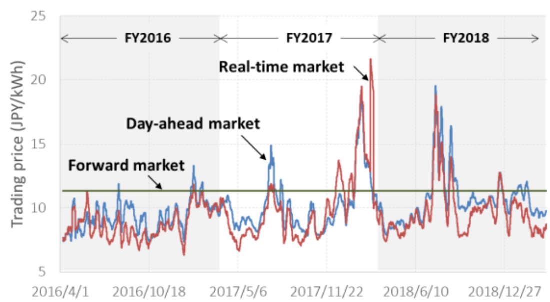

FIGURE 5. Trading price transition (7-day moving average)

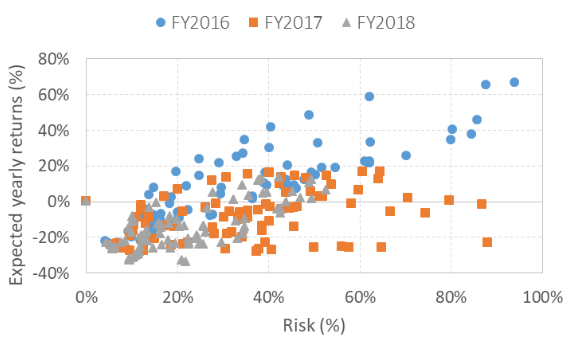

FIGURE 6. Risk-return distribution of all products

frontier) and the expected yearly return (estimated value) for each acceptable risk are derived for the different patterns shown in Table 2. In Table 2, pattern 1 is the case for applying CAPM without ensemble approach (bagging). Pattern 2 is the case for applying CAPM with ensemble approach (bagging) when replaced extraction samples is 1-year and the number of weak learners is 3. Pattern 2 is to confirm the effect of applying ensemble approach. Pattern 3 is to confirm the effect of increasing the number of replaced extraction samples. Pattern 4 is to confirm the effect of increasing the number of weak learners. Next, we derive the return (actual value) when the portfolio of the estimation model is operated for the one-year period of FY2019. Finally, the value estimated with the estimation model was compared with the actual value, and the predictability of the model was evaluated.

TABLE II
VERIFICATION PATTERN

Pattern	Sample no N	Replaced extraction samples no: L	weak learners no: Q
Pattern 1 (w/o bagging)	1,095	–	–
Pattern 2		365	3
Pattern 3		1,095	3
Pattern 4		1,095	5

IV. Results of numerical analysis

The effect of the number of samples and the number of classification estimation models was determined by deriving the efficient frontier of the classification estimation models in different patterns. Figures 7 and 8 show the frontiers obtained with Pattern 2 and Pattern 4. The frontiers are shown in Figures 8 and 9, respectively. It can be seen that efficient frontiers with different trajectories for each classification estimation model are obtained by generating different datasets with low dependency through random extraction with replacement from the original dataset with *N* samples.

With Pattern 2 and Pattern 4, it can be seen that, as the number *L* of replaced samples increases, the difference between the corresponding classification estimation models in the low-risk region (regions with small variance) decreases, and is generally very small. The reason for this could be that, as the number of extractions from replaced extraction samples increases, a relatively larger number of values close to the average return are extracted. In contrast, as the number *L* of replaced extraction samples increases, the difference between the corresponding classification estimation models in the high-risk region (region with large variance) increases. This may be because as the number of extractions from replaced extraction samples increases, more values farther from the average return are extracted.

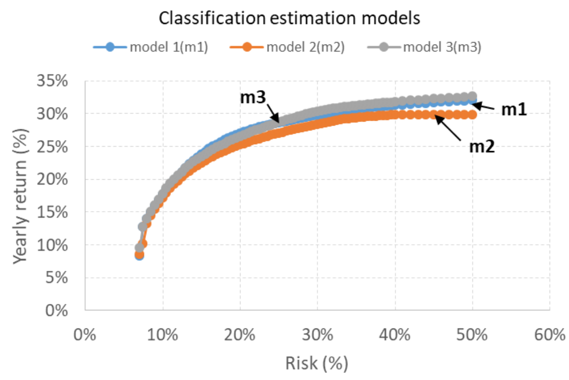

FIGURE 7. Efficient frontier with Pattern 2

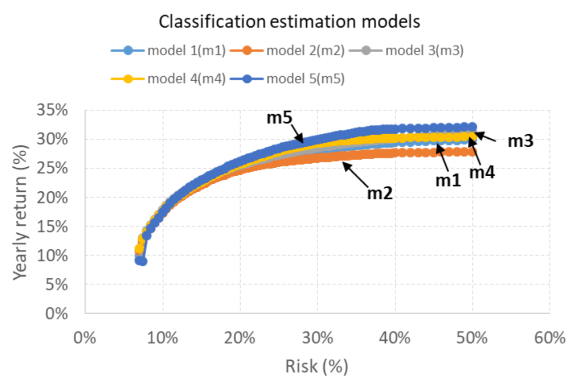

FIGURE 8. Efficient frontier with Pattern 4

Figures 9 to 11 show the relationship between the expected return (estimated value) and actual return (actual value) when the portfolio of the efficient frontier was operated during FY2019. The expected yearly rate for Pattern 1 shows the efficient frontier derived using the three-year historical data of FY2016 to FY2018. In other words, Pattern 1 shows the result without bagging. The expected yearly returns for Pattern 2 and Pattern 3 are the average of the efficient frontiers of the classification estimation model obtained by applying bagging.

In Pattern 1 (Figure 9), the deviation of the estimated value from the average value is large, the mean absolute error (MAE) in the measurement interval is 5.0%, and the maximum value of the absolute error is 8.0%. This is consistent with the conclusion drawn from the results reported in Figure 5, i.e., that it is difficult to predict the yearly expected return for any year with the limited dataset of the past three years because trading prices follow different trends every year.

Pattern 2 (Figure 10) showed some improvement, but due to the small number of replaced samples, the MAE was 4.8% and the maximum absolute error was 9.2%. In Pattern 3 (Figure 11), which had a large number of replaced samples, the error in the high-risk area is small. The MAE and maximum absolute error of Pattern 3 were 2.1% and 4.7%, respectively, which are satisfactory. In areas with a risk below 25%, the absolute error was also less than 2.0%; hence, the predictability of the proposed method may be considered sufficient for practical purposes. On the other hand, in the high-risk area, the maximum value of the divergence of the daily expected return in the measurement interval is approximately 50%, and there is no significant reduction in error. The number of classification estimation

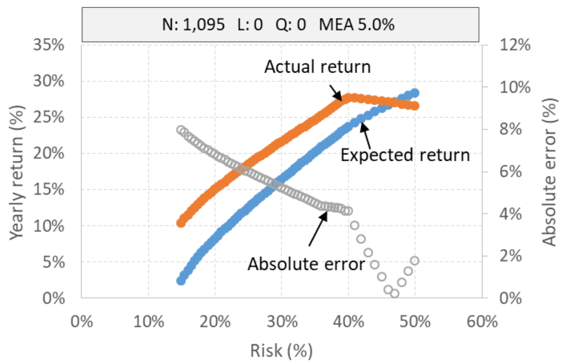

FIGURE 9. Yearly expected return (estimated value) and return (actual value) with Pattern 1

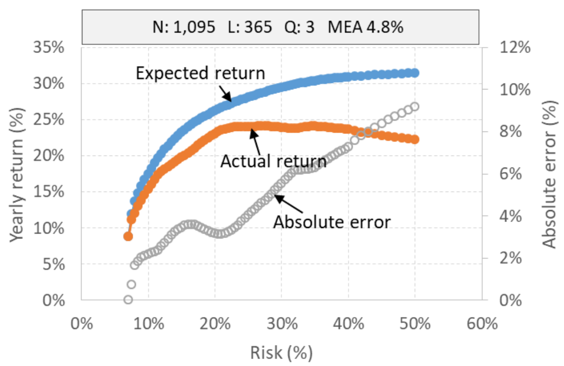

FIGURE 10. Yearly expected return (estimated value) and return (actual value) with Pattern 2

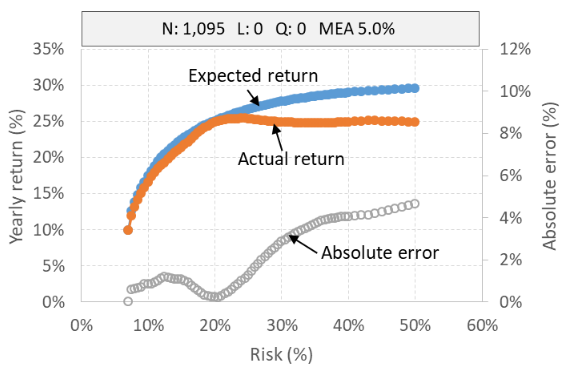

FIGURE 11. Yearly expected return (estimated value) and return

models Q increased from 3 in Pattern 3 to 5 in Pattern 4, but no significant improvement in predictability was observed. The results of all the patterns are summarized in Table 3.

TABLE III
VERIFICATION RESULTS

Pattern	MAE (%)	Maximum absolute error (%)
Pattern 1 (Conventional)	5.0	8.0
Pattern 2	4.8	9.2
Pattern 3	2.1	4.7
Pattern 4	2.9	6.0

Figures 12 and 13 show the discharge power allocation of a BESS on the efficient frontiers of Pattern 1 and Pattern 3. These results show the proportion of the power W of the BESS discharged to the portfolios in the efficient frontier in accordance with the risk allowed by the energy service providers, which is consistent with the result obtained with Equation 17. From the figure, it can be seen that the estimation model in Pattern 3, which was constructed based on multiple different replaced extraction samples using bagging, results in a charge/discharge power portfolio with varied product composition; hence the portfolio has a higher risk diversification effect. In Pattern 1, the discharge power allocation was not considered because the results were not reliable in areas with a risk lower than 15%.

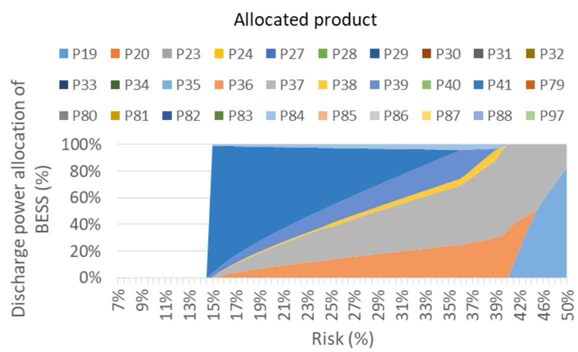

FIGURE 12. Discharge power allocation on the efficient frontier

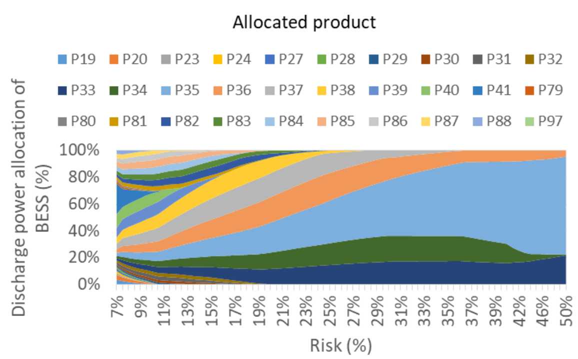

FIGURE 13. Discharge power allocation on the efficient frontier line

V. Conclusion

We proposed a multipurpose operation strategy that efficiently distributes power to multiple power services from a single BESS. With the proposed operation strategy, the allocation of BESS discharge power is determined by using the CAPM and the ensemble Approach, and it is possible to quantitatively evaluate the expected return and risk in BESS operation and achieve the maximum expected return for the selected acceptable risk with higher predictability.

Although there is still room for improvement in predictability in the area of high variance of the return (risk is generally above 20%), the area of low variance of the return (risk is generally below 20%) has very high predictability. However, given that the return peaks at around 20% risk, there is no practical issue. For these reasons, the multi-objective operation strategy proposed in this study can support more efficient operation of energy service providers while providing them with a profit outlook that is appropriate for their acceptable risk.

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KAZUFUMI YUASA (M'2018) was born in Okayama prefecture in Japan on July 27, 1986. He received his B.S. and M.S. degrees in electrical and electronic engineering from the Kyushu Institute of Technology, Fukuoka, Japan in 2009 and 2011, respectively.

He has been an Assistant Manager with the Service Development Division of NTT Facilities, Inc. His research interests include the integration of renewable energy sources and energy control optimization.

Mr. Yuasa is a member of IEEE, IEEJ, IEICE, and IEIEJ.

MIKI UESHIMA was born in Osaka prefecture in Japan, on December 26, 1989. She received her B.S. and M.S. degrees in Sustainable Energy and Environmental Engineering from Osaka University, Osaka, Japan in 2012 and 2014, respectively.

She has been a staff member of the Service Development Division of NTT Facilities, Inc. Her research interests include the integration of renewable energy sources and energy control optimization.

TADATOSHI BABASAKI (M'1999) was born in Nagasaki prefecture in Japan, on October 5, 1965. He received his B.S. and M.S. degrees in electronic engineering and a Ph.D. degree in systems science from Nagasaki University, Nagasaki, Japan in 1988, 1990, and 2011.

He previously worked at the R&D department of NTT Corp. He has been a senior manager with the Service Development Division of NTT Facilities, Inc. His research interests include DC power supply systems for telecommunication and lead acid batteries.

Dr. Babasaki is the chair of IEEE Power Electronics Society Japan Joint Chapter. He is a member of IEEE, IEEJ, and IEICE.

ICHIRO OMURA (M'1993) was born in Iwate Prefecture in Japan on April 13, 1961. He received his B.S. and M.S. degrees in science from Osaka University, Osaka, Japan, in 1985 and 1987, respectively. He received his Ph.D. degree in engineering from the Swiss Federal Institute of Technology (ETH Zurich), Switzerland in 2001.

He previously worked at the R&D Center of Toshiba Corp and Toshiba Semiconductor. He was a guest researcher in ETH Zurich from 1996 to 1997. He has been a Professor in the Graduate School of Life Science and Systems Engineering at the Kyushu Institute of Technology, where he is also a Director of the Next Generation Power Electronics Research Center. His research interests include power electronics and power semiconductor devices.

Prof. Omura is a member of IEEE and IEEJ.