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Development of ESS Scheduling Algorithm to Maximize the Potential Profitability of PV Generation Supplier in South Korea

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Abstract - Under the current policies and compensation rules in South Korea, Photovoltaic (PV) generation supplier can maximize the profit by combining PV generation with Energy Storage System (ESS). However, the existing operational strategy of ESS is not able to maximize the profit due to the limitation of ESS capacity. In this paper, new ESS scheduling algorithm is introduced by utilizing the System Marginal Price (SMP) and PV generation forecasting to maximize the profits of PV generation supplier. The proposed algorithm determines the charging time of ESS by ranking the charging schedule from low to high SMP when PV generation is more than enough to charge ESS. The discharging time of ESS is determined by ranking the discharging schedule from high to low SMP when ESS energy is not enough to maintain the discharging. To compensate forecasting error, the algorithm is updated every hour to apply the up-to-date information. The simulation is performed to verify the effectiveness of the proposed algorithm by using actual PV generation and ESS information.

Keywords: Wind power producers, Energy storage system, Day-ahead market, Progressive hedging method, Offer curve, Rolling horizon method, Multi-stage stochastic optimization.

1. Introduction

The penetration level of Renewable Energy Generation (REG) is consistently increasing to reduce the dependence on fossil fuel and thus, to solve the environmental problems such as global warming and greenhouse effect [1]. Korean government has also set a goal for provision of REG facilities in 'Renewable Energy 3020' plan [2].

However, increasing the penetration level of REG affect adversely on the stability of power system due to the uncertainty and intermittency nature of REG. Energy storage system (ESS) is regarded as one of solutions to solve these problems. Among the various functions of ESS, when ESS is combined with REG, ESS can control the variability of REG, called as 'Renewables Capacity Firming.' Furthermore, when REG produces the large amount of generation at the same time, ESS is able to shift the generation from the generation time to another time, called as 'Renewables Energy Time Shift' [3-6].

In this process, WPPs have studied several methods to build profitable offer curves by overcoming the disadvantages of wind power. In particular, the worst disadvantage is relatively low forecasting accuracy. Although various methods have been studied in order to improve the forecasting accuracy, there is still influential forecasting errors [3]. In the real-time (RT) market, if there is an imbalance between the offer amount and actual generated output, there will be a penalty. Therefore, the WPPs have studied how to build an offer curve that mitigates the effect of uncertainty of wind power on their profits.

However, the existing operation strategy, time-based schedule, has limitation due to the limitation of ESS capacity even though the profits can be maximized with the sophisticated control of ESS. When PV generation is more than enough to charge ESS during the charging period, this operation charges the ESS first and then, the remained PV generation is supplied to the grid regardless of SMP variation. On the other hands, when ESS energy is not enough to maintain the discharging during the discharging period, this operation discharges the ESS first and then, stay due to the limitation of ESS capacity regardless of SMP variation [7].

Since SMP varies every hour, applying the optimal charging and discharging scheduling of ESS is able to increase profits. If ESS is charged when SMP is lower and discharged when SMP is higher, PV-ESS suppliers can capture the wasted additional profits. In this manner, this paper proposes the advanced ESS scheduling algorithm using SMP and PV generation forecasting.

The remainder of this paper is organized as follow: Section 2 describe the current policies and compensation rules for PV generation in South Korea. Under these compensation rules, Section 3 presents the proposed ESS charging and discharging scheduling algorithm by using the SMP and PV generation forecasting. Section 4 presents the case study to verify the effectiveness of the proposed algorithm. Finally, Section 5 explains the conclusion of this paper.

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2. The Current Policies and Compensation Rules for PV Generation in South Korea

To develop the optimal ESS scheduling algorithm, the current policies and compensation rules for PV generation suppliers are investigated. PV generation suppliers can make the profits by selling their generation directly into the electricity market or make a contract of Power Purchase Agreement (PPA) with Korea Electric Power Corporation (KEPCO). The suppliers with PPA are selling their generation to KEPCO without the trading procedure through Korea Power Exchange (KPX). Furthermore, the PPA contract is only applicable if the nameplate of PV generator is less than 1,000 kW. The base price of settlement for PPA is the monthly average of SMP and the trading in electricity market is the actual hourly SMP.

Therefore, in this paper, the algorithm is developed for the suppliers selling their generation into the electricity market based on the hourly SMP because the suppliers with PPA don't require the sophisticated control of ESS since they are compensated based on the monthly average of SMP.

The revenues of the suppliers can be divided into two: SMP revenue and REC revenue. The hourly SMP revenue can be calculated by multiplying the generation of PV-ESS to the hourly SMP as following:

$$revenue_{SMP}(t) = Gen(t) \times SMP(t) \tag{1}$$

where $Gen(t)$ is the generation (kWh) from PV-ESS and $SMP(t)$ is the hourly SMP at time t.

On the other hands, REC revenue is calculated based on a monthly basis. The monthly REC revenue can be calculated by multiplying the weighted REC price to the supplied generation during the month as following:

$$revenue_{REC}(m) = \left(\sum_{t \in m} Gen(t) \right) \times REC_{weight} \times REC(m) \tag{2}$$

where REC_{weight} is the weight based on the installed place, the capacity, and the system configuration in Table 1 [8], $REC(m)$ is monthly REC price.

In this table, it is shown that the government provides the special REC weight 5.0 when PV generation is

Table 1. REC weight for PV generation supplier

Configuration	Weight	Type	Capacity
PV	1.2	Installing on a regular site	<100 (kW)
	1.0		≥100 (kW) <3,000 (kW)
	0.7		>3,000 (kW)
	1.5	Using existing facilities such as buildings	≤3,000(kW)
	1.0		>3,000(kW)
	1.5	Floating on the water surface	
	1.0	Private power generation facilities	
PV-ESS	5.0	Combining with ESS	

combined with ESS, which is much greater than the normal PV generation without ESS. This weight is only applicable when the charged energy of ESS by PV generation between 10:00 and 16:00 (charging period) is discharged between 16:00 and 10:00 (discharging period). Besides, the normal weight of PV generation is applied. Under these rules, this paper introduces new ESS scheduling algorithm to maximize the profits of PV-ESS suppliers.

3. ESS Scheduling Algorithm

Under the current compensation rules for PV-ESS suppliers, the existing operational strategy of ESS, time-based schedule, keep charging the energy from PV generation to ESS during the charging period but keep discharging the energy during the discharging period. However, when PV generation is more than enough to charge ESS during the charging period, this operation charges the ESS first and then, the remained PV generation is supplied to the grid regardless of SMP variation. On the other hands, when ESS energy is not enough to maintain the discharging during the discharging period, this operation discharges the ESS first and then, stay due to the limitation of ESS capacity regardless of SMP variation. Therefore, this section introduces new ESS charging and discharging scheduling algorithm by utilizing the SMP and PV generation forecasting to maximize the profits of PV-ESS generation supplier.

3.1 SMP and PV generation forecasting

PV generation and SMP forecasting algorithm are developed by using a single hidden layer Artificial Neural Networks (ANN) with the input variable selection. Hence, the PV generation forecasting model and SMP forecasting model are developed using the same learning algorithm but the different input variables. The input variables used for PV generation forecasting model are the solar irradiance, temperature, humidity, rainfall rate, sky condition, and the previous generation. Whereas the SMP forecasting model uses the input variables including the forecasted load and the previous SMP. The summary of input variables for the ANN-based forecasting model of PV generation and SMP are presented in Table 2.

Table 2. Summary of input variables for ANN-based forecasting model

Model	Input		Variable
PV generation	Basic	Solar irradiance	I
		Temperature	T
		Humidity	H
		Rainfall rate	R
		Sky condition	S
	(Optional)	n previous generation	$G_{t-1}, \ldots, G_{t-n}$
SMP	Basic	Forecasted Load	L_t
	(Optional)	n previous SMP	$P_{t-1}, \ldots, P_{t-n}$

Among all of these optional input variable candidates, the selection is performed to find the highly correlated input variables with the forecast by using Pearson correlation analysis as following:

$$R_n = \frac{m \times \left(\sum X_n Y\right) - \left(\sum X_m\right) \times \left(\sum Y\right)}{\sqrt{\left(n \times \sum X_m{}^2\right) - \left(\sum X_m\right)^2 \times \left(n \times \sum Y^2\right) - \left(\sum Y\right)^2}} \quad (3)$$

where R_n is the correlation coefficient of n-th variables, X_n is the n-th variable as shown in Table 2, Y is either the PV generation or the SMP, and m is the number of records. The result of the Pearson correlation analysis shows that in addition to the basic input variables, the five of previous PV generation and SMP data can be utilized as input variables since they have a relatively higher correlation coefficient which are more than 0.85.

The ANN model is constructed with one input layer, one hidden layer, and one output layer, as presented in Fig. 1. The input layer consists of the selected input variables obtained by the Pearson correlation analysis. The hidden layer consists of a number of the hidden nodes or so called the transfer nodes. Each node in the hidden layer transforms the summation of the input variable with weight $\theta^{(1)}$. The number of nodes is determined through cross-validation optimization, and the activation function used in this study is 'Softplus' function which is suitable for forecasting problem. Whereas, the output layer is the forecasted value which is the summation of the transfer nodes with weight $\theta^{(2)}$.

The ANN-based PV generation and SMP forecasting model can be mathematically expressed as follows:

$$Y_t = \theta_0^{(2)} + \sum_{i=1}^{NHL} \left(\theta_i^{(2)} \cdot \ln\left(1 + \exp(\theta_{0i}^{(1)} + \sum_{n=1}^{N} (\theta_{ni}^{(1)} \cdot X_n))\right)\right) \quad (4)$$

where Y_t is the forecasted PV generation or SMP at time t, X_j is the input variable of each model, NHL is the number of nodes in the hidden layer, and $\theta^{(1)}$ and $\theta^{(2)}$ are the ANN model parameters at each layer. The ANN model parameters ($\theta^{(1)}$ and $\theta^{(2)}$) can be obtained through the learning algorithm by minimizing the error between the actual and forecasted results. The learning optimization algorithm to find the ANN model parameters is defined as follows:

$$\min_{\Theta_{nl}^{(1)}, \Theta_l^{(2)}} \frac{1}{2m}\left(-\left(\sum_{i=1}^{m}\left(Y_{t,actual} - Y_{t,forecast}\right)^2\right) + \lambda\left(\sum_{l=1}^{L-1}\sum_{j=1}^{J}\sum_{k=1}^{J+1}\left(\Theta_{kj}^{(l)}\right)^2\right)\right] \quad (5)$$

where m *is* number of records, L is number of layer in the ANN which is 3, J is the number of node in each layer, and λ is the regularization parameter of the learning algorithm.

The ANN-based forecasting model is a dependent on the training dataset, which means different training dataset will result in different model with different accuracy. It also depends on the selected number of hidden nodes and the value of regularization parameter. Therefore, the final ANN-based forecasting model for PV generation and SMP is obtained through k-fold cross-validation (kCV) optimization technique. The kCV aims to find the optimized model by selecting the combination of the learning dataset, the number of the hidden nodes (NHL) and the regularization parameter (λ). The optimization problem is formulated as follows:

$$\min_{D, NHL, \lambda, \Theta} \left(\frac{1}{m} \sum_{i=1}^{m} \left(y_{actual}^{(i)} - y_{predict}^{(i)}\left(D, NHL, \lambda\right)\right)^2 \right) \quad (6)$$

where m is the number of the data in the data subset D.

In the kCV technique, the training dataset is divided into k subset, then the model is trained by using k-1 subset, so called D subset, and validated by using the remaining subset, so called the cross-validation (CV) subset. For each pair of D-CV subset, various value of number of the hidden layer (NHL) and the regularization parameter (λ) are used. The Mean Square Error (MSE) at each step is calculated and recorded. The model with the lowest MSE is selected

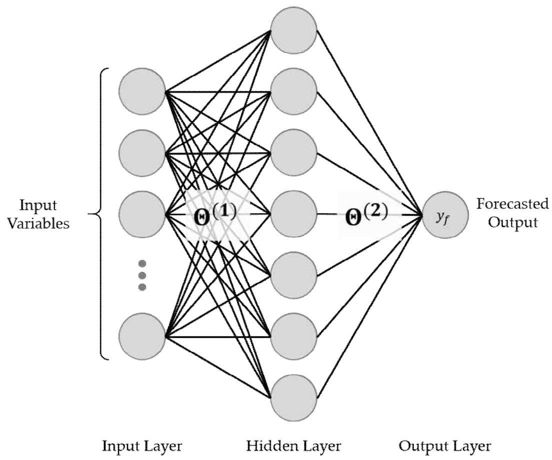

Fig. 1. The architecture of ANN model

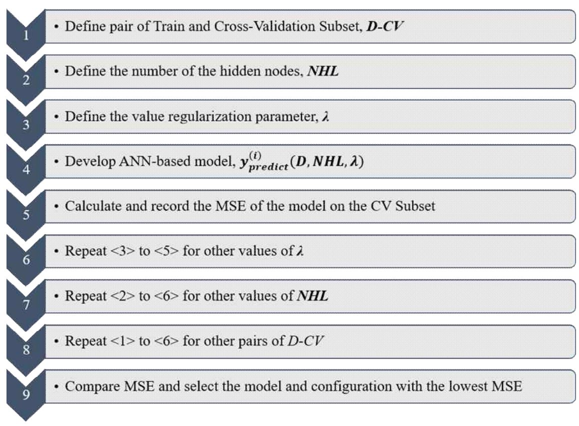

Fig. 2. kCV optimization procedure

as the final model. The overall steps of the kCV optimization technique is presented in Fig. 2.

3.2 ESS scheduling algorithm

Under the existing compensation rules, the charging and discharging operation of ESS is determined based on the time period whether it is in the charging period or not. Therefore, the charging operation of ESS is only scheduled in the charging period but the discharging operation in the discharging period. The proposed algorithm provides the ESS schedule based on these charging and discharging periods. When the end of charging and discharging periods are included in 24-hour forecasting time period, it provides the complete schedule of ESS, otherwise, it is not able to schedule the ESS operation because of the insufficient forecasting information by the end of the period. Based on this, this section introduces the new ESS scheduling algorithm to maximize the potential profitability for PV-ESS generation supplier.

3.2.1 ESS charging scheduling in charging period

The proposed ESS scheduling algorithm is to maximize the profits by ranking the charging schedule from low to high SMP when PV generation is more than enough to charge ESS. Therefore, the algorithm determines when is the good time to charge ESS by the ranks based on SMP forecasts.

Table 3 shows the example of ranking the charging time based on SMP forecasts. The charging time is ranked from low to high SMP forecasts. In this day, the lowest SMP is forecasted at 13:00 which is the good time to charge ESS instead of selling the redundant PV generation to the grid with lowest SMP. On the other hand, the highest SMP is forecasted at 15:00 which is the good time to sell the PV generation if PV generation needs to sell its generation directly to the grid due to the redundancy. Furthermore, when the same SMP is forecasted, the higher rank is assigned to the near time because the accuracy of the near time forecasting is better so that it can reduce the risk that ESS is not fully charged at the end of the charging period.

Table 3. Ranking the charging time based on SMP forecasts

Time	10:00	11:00	12:00	13:00	14:00	15:00
SMP	97.9	97.9	97.0	96.8	97.7	98.3
Rank	4	5	2	1	3	6

The scheduling period for the charging is from the current time to the end of the charging period. After ranking the charging time, the algorithm checks the current ESS status how much ESS needs to be charged to make the full capacity of ESS at the beginning of the discharging period because REC profits obtained from the discharging energy of ESS in the discharging period is greater than SMP profits obtained from selling the PV generation directly to the grid in charging period. Then, the available PV generation to charge ESS using PV generation forecasts is calculated by considering the charging efficiency and the rating of power conversion system (PCS) as following:

$$PV_{ESS}(t) = \min(P_{PV}(t) \times \varepsilon_{Ch}, PCS \times \varepsilon_{Ch}) \quad (7)$$

where ε_{Ch} is the charging efficiency of ESS, PCS is the rating of PCS.

Using the available PV generation and the rank of the charging time, the algorithm determines when ESS needs to be charged by PV generation. Every iteration of the algorithm sums the available PV generation from the high rank to low rank of the charging time until it is greater than the available capacity of ESS as following:

$$ESS_{rem,charge} \le \sum_{Rank=1}^{N} PV_{ESS}(Rank) \quad (8)$$

where $ESS_{rem,charge}$ is the available capacity of ESS for the charging.

The algorithm finds the first rank (N) over the available capacity of ESS for the charging and then, it determines the charging time if the rank is greater than or equals to N . If the remaining PV generation after charging ESS is available at N-th rank, it is supplied directly to the grid. The overall flowchart of ESS charging scheduling in charging period is shown in Fig. 3.

3.2.2 ESS discharging scheduling in discharging period

ESS discharging scheduling determines the time to discharge the energy to the grid by ranking the discharging

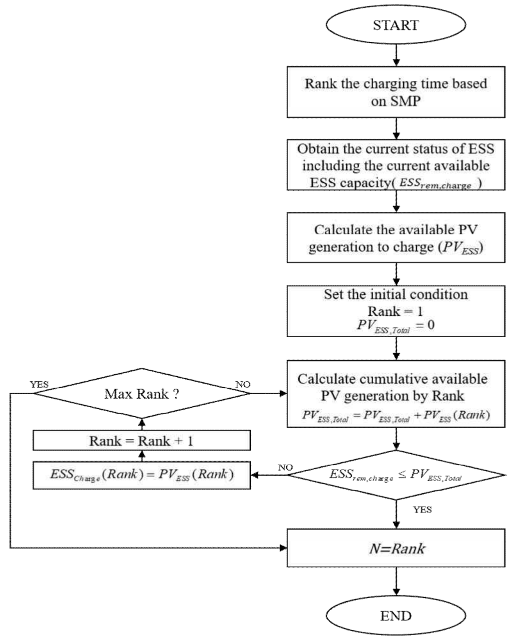

Fig. 3. Flowchart of ESS charging scheduling in charging period

Table 4. Ranking the discharging time based on SMP forecasts

Time	16:00	17:00	18:00	19:00	20:00	21:00
SMP	102.6	102.5	103.8	103.7	103.4	103.2
Rank	7	8	1	2	3	4
Time	22:00	23:00	0:00	1:00	2:00	3:00
SMP	98.2	101.3	101.3	101.3	101.6	101.6
Rank	18	12	13	14	9	10
Time	4:00	5:00	6:00	7:00	8:00	9:00
SMP	102.9	102.9	101.4	100.4	99.0	99.3
Rank	5	6	11	15	17	16

schedule based on SMP forecasts. However, on the contrary to the charging scheduling, the higher rank and lower rank are assigned when higher and lower SMP are forecasted respectively.

The example of ranking for the discharging schedule based on SMP forecasts is shown in Table 4. In this table, the highest SMP is forecasted at 18:00 which is the good time to sell the ESS energy to the grid to maximize the SMP revenue. On the other hands, the lowest SMP is forecasted at 22:00 which is better to stay if ESS is able to discharge all of its energy in another time. Like the charging scheduling, when the same SMP is forecasted, the higher rank is assigned to the near time because the accuracy of the near time forecasting is better so that it can reduce the risk that ESS is not fully discharged at the end of the discharging period.

The scheduling period for the discharging is between the current time and the end of the discharging period. After ranking the discharging time, the algorithm obtains the remaining capacity of ESS. Then, the algorithm determines when ESS needs to be discharged. Every iteration of the algorithm sums the maximum ESS discharging energy by PCS from the high rank to low rank of the discharging time until it is greater than the remaining capacity of ESS as following:

$$ESS_{rem,discharge} \leq N \times PCS \tag{9}$$

where $ESS_{rem,discharge}$ is the remaining capacity of ESS for the discharging, PCS is the rating of PCS.

The algorithm finds the first rank (N) over the remaining capacity of ESS for the discharging and then, it determines the discharging time if the rank is greater than or equals to N. If the remaining ESS energy is smaller than the maximum ESS discharging energy at N-th rank, the remaining ESS energy is only discharged fully to the grid. The flowchart of ESS discharging scheduling in discharging period is shown in Fig. 4.

3.2.3 The combined ESS scheduling

The overall flowchart of the combined ESS scheduling of the charging and discharging is shown in Fig. 5. First, it performs SMP forecasting to determine the rank of charging and discharging time in the scheduling algorithm.

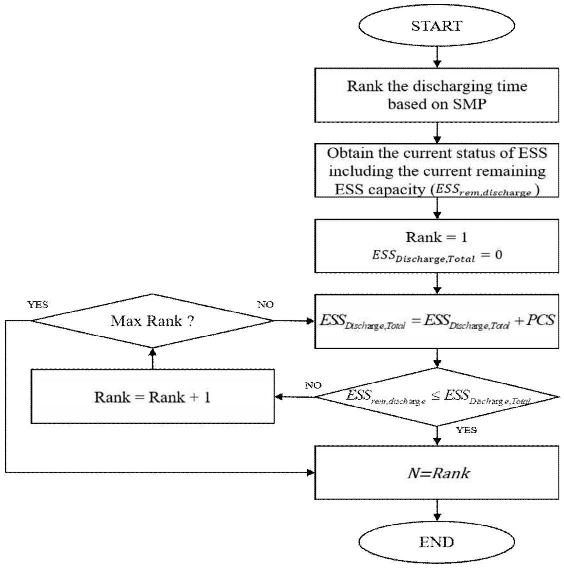

Fig. 4. Flowchart of ESS discharging scheduling

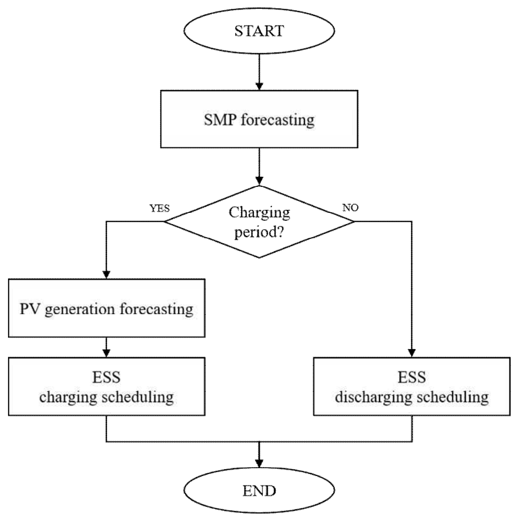

Fig. 5. Flowchart of the combined ESS scheduling

Then, it determines whether the current time lies in the charging period or discharging period. If the current time is within the charging period, it performs the PV generation forecasting and then, carries out the ESS charging scheduling. Otherwise, it carries out the ESS discharging scheduling. Note that PV generation forecasting is not performed in the discharging period because PV generation in this period is directly supplied to the grid without passing through ESS so that it is not necessary to consider it to schedule the discharging of ESS.

It is important to guarantee that ESS is fully charged and discharged at the end of the charging and discharging period respectively because REC revenue is much greater than SMP revenue. Therefore, to reduce the risk coming from the effect of PV generation and SMP forecasting error, the algorithm is updated every hour to apply the up-to-date information of PV generation and ESS. In addition, one additional redundancy charging is scheduled in order to prevent that ESS is not fully charged due to the forecasting error of PV generation.

4. Simulation Results

The simulation is performed to verify the effectiveness of the proposed algorithm by using actual PV generation and ESS information as shown in Table 5 and the corresponding SMP and REC data. PV generation data from 4/1/2017 to 4/9/2018 is obtained from the actual 100 kW PV generator installed in Jeju island in South Korea. The previous one year of data is used to develop the forecasting model for both SMP and PV generation.

This site doesn't include ESS and thus, it is assumed that ESS including 300 kWh battery and 100 kW PCS is installed at this site for the simulation. The typical size of battery and PCS is selected for the simulation, that the size of battery and PCS is three-times greater than and equal to the one of PV generator respectively. The efficiency of the charging and discharging is also considered as 90% and 99% respectively.

4.1 Results of PV generation and SMP forecasting

4.1.1 SMP Forecasting

The SMP forecasting algorithm is developed to rank the charging and discharging time. Fig. 6 shows the results of daily SMP forecasting in Jun. 04, 2017 [9]. It is shown that the results of the SMP forecasting can follow the patterns of SMP so that it can be utilized to rank the schedule of ESS. Note that SMP is higher during daytime than nighttime in general but the opposite trend is observed in the selected day.

Table 5. ESS and PV generation information used for the simulation

ESS Information	Value
Battery Capacity (BAT)	300 kWh
PCS Capacity (PCS)	100 kW
Charging Efficiency (ε_{Ch})	90 %
Discharging Efficiency (ε_{DCh})	99 %
PV Generation Information	Value
PV capacity	100 kW

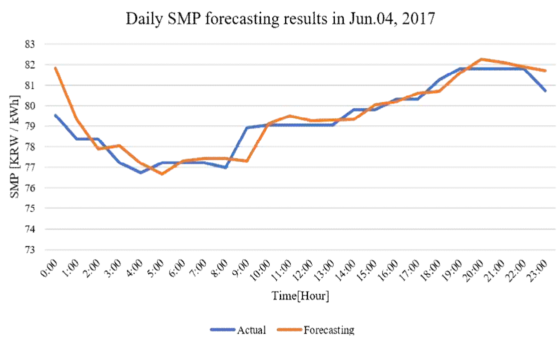

Fig. 6. Daily SMP forecasting results in Jun. 04, 2017

The overall performance of SMP forecasting is shown in Table 6 by using monthly and total Mean Absolute Percentage Error (MAPE). In this table, the greater MAPE is observed during the summer season than the others. The total MAPE in the entire simulation period is observed as 3.35 %.

4.1.2 PV Generation forecasting

The PV forecasting algorithm is also developed to estimate how much PV generation can charge ESS in the charging period. The results of daily PV generation forecasting in Oct. 15, 2017 are shown in Fig. 7. While forecasting PV generation is not perfectly matched with actual one, it is able to follow the patterns of PV generation so that it can be utilized to estimate the charging energy of ESS from PV generation.

The overall performance of PV generation forecasting is shown in Table 7. In this table, the total MAPE in the entire

Table 6. The overall performance of SMP forecasts

Month	Monthly MAPE	Month	Monthly MAPE
04/2017	5.31 %	11/2017	2.58 %
05/2017	3.31 %	12/2017	2.08 %
06/2017	2.31 %	01/2018	2.17 %
07/2017	4.52 %	02/2018	2.61 %
08/2017	5.29 %	03/2018	1.20 %
09/2017	5.87 %	04/2018	1.22 %
10/2017	5.01 %		
		Total	3.35 %

Table 7. The overall performance of PV forecasting result

Month	Monthly MAPE	Month	Monthly MAPE
04/2017	13.95 %	11/2017	12.35 %
05/2017	12.56 %	12/2017	19.26 %
06/2017	7.30 %	01/2018	19.77 %
07/2017	12.34 %	02/2018	18.05 %
08/2017	12.60 %	03/2018	12.05 %
09/2017	13.77 %	04/2018	11.48 %
10/2017	17.27 %		
		Total	14.06 %

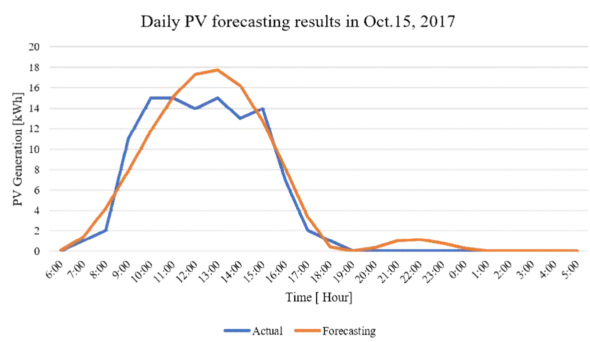

Fig. 7. Daily PV generation forecasting results in Oct. 15, 2017

simulation period is observed as 14.06 % which is less accurate than SMP forecasting. In overall, it can be found that although the performance of the forecasting algorithms is the moderate, it is necessary to reduce the risk coming from the effect of PV generation and SMP forecasting error. Therefore, the algorithm is updated every hour to apply the up-to-date information of PV generation and ESS because the accuracy of the near time forecasting is better than the long-term forecasting.

4.2 Results of the reference case

Two references cases are developed to verify the proposed algorithm. Reference cases are PV only system without ESS and PV-ESS system with the existing operational strategy of ESS.

4.2.1 PV only system without ESS

In the case of PV generator alone, 1.1999 REC weight is applied based on the PV capacity but PV-ESS REC weight is not applicable. In the simulation period, the SMP, REC, and total revenues are shown in Table 8. In this table the SMP, REC, and total revenues are observed as 9.02 million KRW, 17.47 million KRW, and 26.49 million KRW respectively. It can be found that the REC revenue is approximately twice greater than SMP revenue.

Table 8. Revenue of PV only system without ESS

Month	Revenue (Unit: 10^3 KRW)		
	SMP Revenue	REC Revenue	Total Revenue
04/2017	744.7	1276.6	2021.3
05/2017	975.4	1813.4	2788.8
06/2017	400.7	675.1	1075.8
07/2017	788.3	1525.8	2314.1
08/2017	925.8	1924.7	2850.5
09/2017	678.7	1610.0	2288.7
10/2017	654.1	1822.7	2476.8
11/2017	494.0	1080.7	1574.7
12/2017	742.2	1646.4	2388.6
01/2018	717.3	1056.5	1773.7
02/2018	696.8	1559.3	2256.2
03/2018	990.3	1184.3	2174.6
04/2018	210.4	298.1	508.5
Total	9018.6	17473.6	26492.3

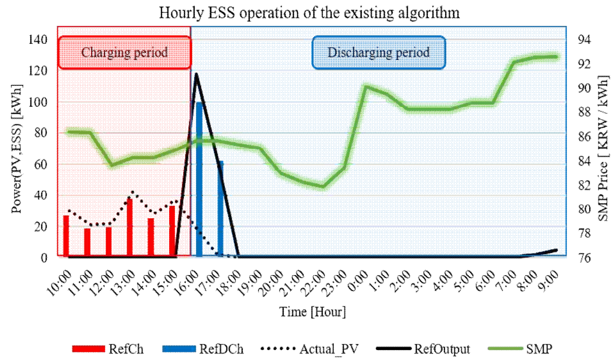

Fig. 8. Hourly ESS operation of the existing algorithm

4.2.2 PV-ESS system with the existing operational strategy of ESS

PV-ESS system with the existing operational strategy of ESS keeps charging the energy from PV generation to ESS during the charging period but keep discharging the energy during the discharging period. The hourly ESS operation of the existing algorithm in Nov. 30, 2017 is shown in Fig. 8. It is shown that the existing algorithm charges all of PV generation in the charging period and ESS is discharged as soon as it enters in the discharging period. The figure also shows the SMP. Although ESS can be discharged when SMP is higher, the existing algorithm discharges ESS in relatively lower SMP period.

To calculate the REC revenue, 1.1999 REC weight is applied when PV generation is directly supplied to the grid, but 5.0 REC weight is applied when the charged energy of ESS by PV generation in charging period is discharged in discharging period. In the simulation period, the SMP, REC, and total revenues are shown Table 9. It is observed that the SMP revenue is KRW 8.40 million KRW, which is about 7% less than the case of PV only system because of the reduced energy by the charging and discharging efficiency of ESS operation and the time shifted generation to the lower SMP time period. However, the REC revenue is observed as 52.97 million KRW, showing about 303 % greater than the case of PV only system. Finally, the total revenue is observed as 61.37 million KRW, which is about 232 % greater than the previous case. In summary, the total revenue increases very much because of the increase of REC revenue thanks to the special REC weight 5.0 of PV-ESS.

4.3 Results of the proposed ESS scheduling algorithm

To verify the operation of ESS with the proposed algorithm, the hourly ESS operation in same day of the proposed algorithm is compared, as shown in Fig. 9. It is shown that the charging operation of ESS in the charging

Table 9. Revenue of PV-ESS system with the existing operational strategy of ESS

Month	Revenue (Unit: 10^3 KRW)		
	SMP Revenue	REC Revenue	Total Revenue
04/2017	699.7	3591.8	4291.6
05/2017	922.0	5084.7	6006.6
06/2017	373.6	1914.8	2288.4
07/2017	729.1	4427.9	5157.0
08/2017	856.6	5669.1	6525.7
09/2017	637.1	4901.8	5538.9
10/2017	624.9	5636.3	6261.2
11/2017	458.1	3449.1	3907.2
12/2017	682.7	5436.0	6118.7
01/2018	661.9	3491.7	4153.6
02/2018	646.6	4955.1	5601.7
03/2018	916.6	3516.4	4433.1
04/2018	195.3	895.9	1091.2
Total	8404.2	52970.6	61374.7

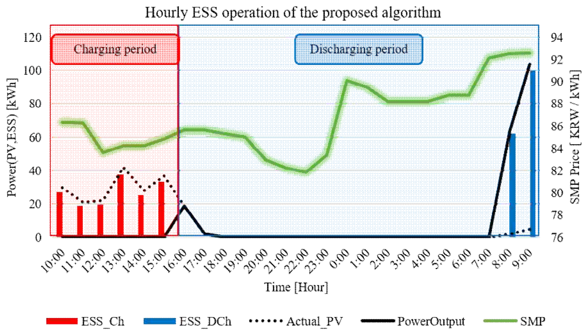

Fig. 9. Hourly ESS operation of the proposed algorithm

Table 10. Revenue of PV-ESS system with the proposed algorithm

Month	Revenue (Unit: 10^3 KRW)		
	SMP Revenue	REC Revenue	Total Revenue
04/2017	703.0	3539.2	4242.1
05/2017	947.6	5145.6	6093.2
06/2017	375.0	1914.8	2289.8
07/2017	731.6	4427.9	5159.5
08/2017	848.1	5599.6	6447.7
09/2017	652.5	4976.4	5628.9
10/2017	632.5	5636.3	6268.8
11/2017	448.9	3330.6	3779.4
12/2017	692.7	5487.5	6180.2
01/2018	675.2	3547.6	4222.8
02/2018	662.6	4952.8	5615.4
03/2018	917.9	3468.0	4385.9
04/2018	207.4	948.4	1155.8
Total	8494.9	52974.6	61469.5

period is same with the one of previous case because the amount of PV generation is not enough to fully charge ESS in this day. Because of the large size of ESS, ESS is not fully charged in most of the day in simulation period. However, if the amount of PV generation is more than enough to charge ESS, the proposed algorithm schedules the charging operation in less expensive SMP time. If such a case occurs, the revenue gap by SMP will increase. Furthermore, the different discharging operation of ESS is observed. Unlike the existing algorithm, the proposed algorithm searches for the higher SMP time to discharge its energy optimally.

In the simulation period, the SMP, REC, and total revenues of PV-ESS system with the proposed algorithm are shown in Table 10. SMP revenue is observed as 8.49 million KRW, is about 5.81 % less than PV only system but about 1.08 % greater than PV-ESS system with the existing algorithm. REC revenue is observed as 52.97 million KRW, which is 203.17 % greater than PV only system but almost same with PV-ESS with the existing system.

Although same generation from PV generator and ESS is supplied to the grid with the case of the existing algorithm, the slight difference in REC revenue is observed because of the shifted generation month by month. Finally, total revenue is observed as 61.47 million KRW, which is about 132.03 % greater than PV only system and about 0.2 % greater than PV-ESS system with the existing algorithm. In summary, because of the large benefit of REC and the moderate variation of SMP in a day, the total revenue is not improved much.

5. Conclusion

In this paper, new ESS scheduling algorithm for PV generation suppliers is proposed by utilizing the SMP and PV generation forecasting. The proposed algorithm determines the charging time of ESS by ranking the charging schedule from low to high SMP when PV generation is more than enough to charge ESS during the charging period. The discharging time of ESS is determined by ranking the discharging schedule from high to low SMP when ESS energy is not enough to maintain the discharging during the discharging period.

The simulation is performed to verify the effectiveness of the proposed algorithm by using actual PV generation and ESS information. It is shown that the proposed algorithm is able to increase the revenues of PV generation suppliers. However, because of the large benefit of REC and the moderate variation of SMP in a day, the total revenue is not improved much. When the REC benefit is gradually reduced and SMP varies by increasing the amount of REG in the future, this proposed algorithm will effectively increase the revenues of the PV-ESS suppliers.

The further study about optimization of ESS capacity is necessary if the proposed algorithm is able to reduce the size of ESS and thus, the system capital cost.

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