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Effect of Random Forest vs. Exponential Smoothing Forecasting Method on Solar Energy Management Using On-Demand Cumulative Control Method

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Abstract

In recent years, global warming has become more serious problem because the amount of greenhouse gas (GHG) emissions is increased. Therefore, renewable energy such as solar energy should be utilized effectively to reduce GHG emissions. However, it is difficult to balance the supply and demand for solar energy because the output depends on the weather. The on-demand cumulative control method is the method of inventory control to balance between supply and demand dynamically. The on-demand cumulative control method involves the phase of forecasting power generation and consumption in order to estimate the effective power supply. However, when they are not taken into account the precision of forecasting electricity supply and demand, the appropriate demand-to-supply management might be difficult. This study analyzes the forecasting method in solar energy demand-to-supply management by comparing the exponential smoothing method and the random forest is implemented under the same explanatory variables in terms of the precision of forecasting power generation and consumption. Moreover, temperature, date, weekdays or holidays, and period of time are set as explanatory variables and the effect of setting them is evaluated. Finally, the total power purchase amount is investigated using the on-demand cumulative control method.

Keywords
supply and demand forecasting, machine learning, electricity demand-to-supply management, hourly analysis, and inventory control.

1. Introduction

In recent years, global warming has become more serious problem around the world, and it has caused various environmental problems. The cause of them is the greenhouse gases (GHG) emissions. Therefore, the reduction of GHG emissions is required. One of the means to reduce GHG emission is increasing usage of renewable energy.
In production and logistics, solar energy is one of the renewable energies and has been promoted as an effective means to avoid using fossil fuels that generate GHG emissions. This is because, 25.3% of GHG emissions are occurred from the production sector in Japan. (Ministry of the Environment and National institute for Environmental Studies 2023). In order to overcome this problem, renewable energy should be used actively in the field of supply chain. However, it is difficult for using solar energy to balance the supply and demand owing to the characteristic s of solar power generation. The amount of solar power that can be generated depends on the availability of sunlight. One of the solutions to address to stabilize the solar power supply is using storage battery. However, storage battery has some problems. For example, the amount of electricity which can be stored in storage battery is limited. Additionally, introducing the large-capacity batteries are very expensive. Therefore, demand-to-supply management is necessary for implementing the effective usage of solar energy and balancing the electricity supply and demand. Moreover, random forest, one of the machine learning algorithms can identify the trend and complex relationship by learning and adapting from large volume of data (Ledmaoui et al. 2023). Thus, machine learning has the potential of improving the forecasting precision by training on historical power generation or consumption data. According to the previous studies, several machine learning models are used to improve the renewable energy management. However, there is a lack of study on the analysis of introducing machine learning for dynamic demand-to-supply management.

1.1 Purpose of this study

This study aims to analyze the effect of the difference of forecasting method in solar energy demand-to-supply management at the distribution center, which is the target facility. Moreover, random forest is applied for forecasting power generation and consumption. Additionally, the comparison between the effect of the difference between applying the exponential smoothing method and applying random forest. Proposed method could calculate the appropriate power purchase amount on demand, which takes into account the change in the trend of electricity demand and seasonality. Moreover, it contains the process of forecasting power generation and consumption. The comparison of forecasting method between using the exponential smoothing method and random forest is implemented in terms of the forecasting precision and effect on the power purchase amount. Therefore, the results can estimate the effective forecasting method in terms of the solar energy demand-to-supply management at the distribution center.

2. Literature Review

Regarding renewable energy management, Pereira and Silva (2024) developed the machine-learning algorithm for fault classification and monitoring photovoltaic inverters to achieve solar energy farms more efficient. This algorithm improved the photovoltaic energy production and monitoring condition by the monitorization and optimization of the inverter. However, they did not mention about energy demand-to-supply management. Behzadi et al. (2023) proposed the management of smart building energy systems that minimize the carbon footprint and increase usage of solar and biomass energy. The result of their study shows that the solution enables repayment of the energy purchase amount during cloudy days and nights through the sale of excess renewable energy production. However, they did not consider the trend of power consumption and changing it.

For the forecasting, Rentizelas et al. (2012) analyzed the effect that multiple scenarios for the change in emission allowance cost had on the future power generation mix of Greece. They formed a forward-sweeping linear programming model and minimized the annual cost required to generate excess energy. Moreover, they forecasted the period when renewable energy will be more cost-effective than using fossil fuel. However, they did not conduct solar energy demand-to-supply management monthly or seasonally. Ledmaoui et al. (2023) investigated an efficient model for forecasting power generation by comparing several machine learning algorithms. They showed that, artificial neural network was the most effective energy forecasting model. However, they did not consider balancing solar power generation and consumption.

With respect to energy demand-to-supply management, Kato et al. (2022) applied a job shop control policy to the power generation and consumption data in the childcare facility perform solar energy demand-to-supply management. Ijuin et al. (2022) conducted the solar energy demand-to-supply management by applying an on-demand cumulative control method (Matsui et al. 2005) to actual solar power generation and consumption data in a childcare facility. They showed that applying an on-demand cumulative control method reduce the power purchase amount. However, in both studies, annually solar energy demand-to-supply management are not implemented. This is because, data collection was limited to only one week. Moreover, they only evaluated one type of season and facility in their studies, even though weather condition is are seasonal.

3. Methods

3.1 Procedure for Overall Analysis

Figure 1 shows the analysis procedure of this study. The procedures comprise five steps.
The first step involves analyzing the effect of applying random forest on forecasting power generation and consumption. Comparing the application of random forest and the exponential smoothing method with the precision of forecasting are implemented as a means of analyzing it.In the second step, the effect of the difference of explanatory variables was evaluated when using random forest in order to investigate the effect of the characteristics of the period and climate on the precision of forecasting power generation and consumption.

In the third step, the hourly analysis of power generation and consumption data is implemented in order to investigate the hourly precision of forecasting power generation and consumption. The fourth step applies the on-demand cumulative control method to the annual solar power generation and consumption data for forecasting power generation and consumption and estimating the total power purchase amount. In the final step, the effect of changing the method of forecasting power generation and consumption is analyzed by comparing between random forest and the exponential smoothing method in terms of the total power purchase amount based on the results of the on-demand cumulative control method.

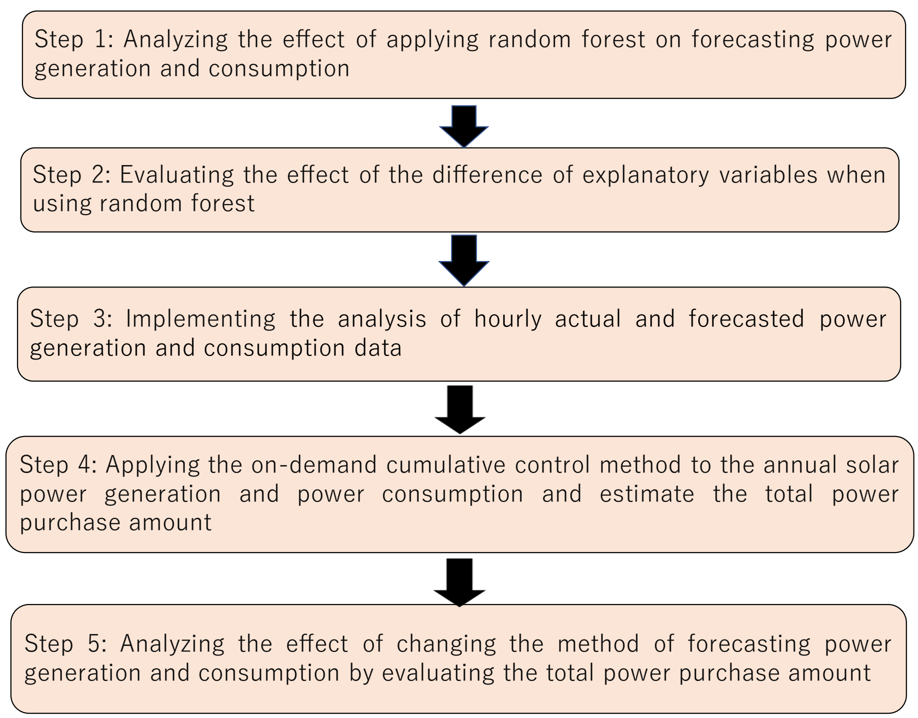

Figure 1. The analysis procedure of this study

3.2 Procedure for Applying the On-Demand Cumulative Control Method

In this study, solar energy demand-to-supply management is implemented by applying the on-demand cumulative control method to the estimated power generation and actual power consumption data at a distribution center. The on-demand cumulative control method is a dynamic demand-to-supply management method based on the inventory control proposed by Matsui et al. (2005). Demand-to-supply management is performed dynamically by using the on-demand cumulative control method. In this study, solar energy demand-to-supply management is implemented and analyzed to estimate the effect on total power purchase amount. Notations used in this study are written as shown in

Table 1. Moreover, Figure 2 shows the procedure for applying the on-demand cumulative control method. The procedure for applying the on-demand cumulative control method of Takada et al. (2024) is followed.

Table 1. Notations used in this study

Varibles	
O_t	Power consumption in period t [kWh]
N_t	Moving base storage amount in period t [kWh]
L_t	Remaining storage amount in period t [kWh]
$\overline{\beta_t}$	Input amount determination parameter in period t
S_t	Power generation in period t [kWh]
λ_t	Demand rate at period t
P_t	Power purchase amount in period t [kWh]
I'_t	The amount of power supply in the next period in period t [kWh]
X_t	Forecasted power consumption when using the exponential smoothing method [kWh]
Y_t	Forecasted power generation when using the exponential smoothing method [kWh]
X_t^{RF}	Forecasted power consumption when using the random forest [kWh]
Y_t^{RF}	Forecasted power generation when using the random forest [kWh]
L_{init}	Initial storage amount [kWh]
HAm_t	Total solar irradiation in period t per array plane [kWh/m^2]
Coefficient	
α	Smoothing coefficient used in the exponential smoothing method
K	The coefficient total design factor
PAS	Panel power generation capacity [kW]
Gs	Standard irradiance per array plane [kW/m^2]

In step (a), the estimated amount of solar power generation S_t is calculated as shown in Equation (1) (Kurokawa et al. 2016). The coefficient total design factor K, the panel power generation capacity PAS, the total solar irradiance in the period t per array plane HAm_t, and standard irradiance per array plane Gs are used in Equation (1).

$$S_t = K \cdot PAS \cdot \frac{HAm_t}{Gs} \tag{1}$$

In step (b), the following parameters are set to their initial values: coefficient α $(0 \leq \alpha \leq 1)$ used in the exponential smoothing method (Asada et al. 2004), initial input amount determination parameter $\overline{\beta_0}$ $\left(0 \leq \overline{\beta_0} \leq 1\right)$, initial storage amount L_{init}, and cumulative probability distribution with charge amount L_t, $F(L_t)$.

In step (c), the forecasted power consumption X_{t+1} and power generation Y_{t+1}, respectively, are calculated using the exponential smoothing method (Asada et al. 2004) and random forest. When the exponential smoothing method is applied, the calculation uses the power consumption over period t, O_t, and power generation over period t, S_t, as expressed in Equations (2) and (3). On the other hand, the same forecasting is implemented with using random forest and the forecasted power consumption X_{t+1}^{RF} and power generation Y_{t+1}^{RF}, respectively, are calculated. When random forest is applied, explanatory variables are set and forecasting are implemented by programming with python.

$$X_{t+1} = \alpha O_t + (1-\alpha)X_t \tag{2}$$

$$Y_{t+1} = \alpha S_t + (1-\alpha)Y_t \tag{3}$$

In step (d), the moving base storage amount N_t is estimated as shown in Equation (4).

$$N_t = F^{-1}\left(\overline{\beta_t}\right) \tag{4}$$

In step (e), updating the input amount determination parameter over period t, $\overline{\beta_t}$ is implemented using the demand rate over a period t, λ_t, as shown in Equation (5) (Matsui et al. 2009).

$$\bar{\beta}_{t+1} = \frac{\lambda_t}{\lambda_{t+1}}\overline{\beta_t} \tag{5}$$

In step (f), Equation (6) shows the amount of power supply in the next period in period t, I'_{t+1}, which is the final output of the on-demand cumulative control method in inventory management (Matsui et al. 2005).

$$I'_{t+1} = X_{t+1} + N_t - L_t \tag{6}$$

In step (g), the power purchase amount in next period P_{t+1} is calculated using Equation (7).

$$P_{t+1} = I'_{t+1} - Y_{t+1} \tag{7}$$

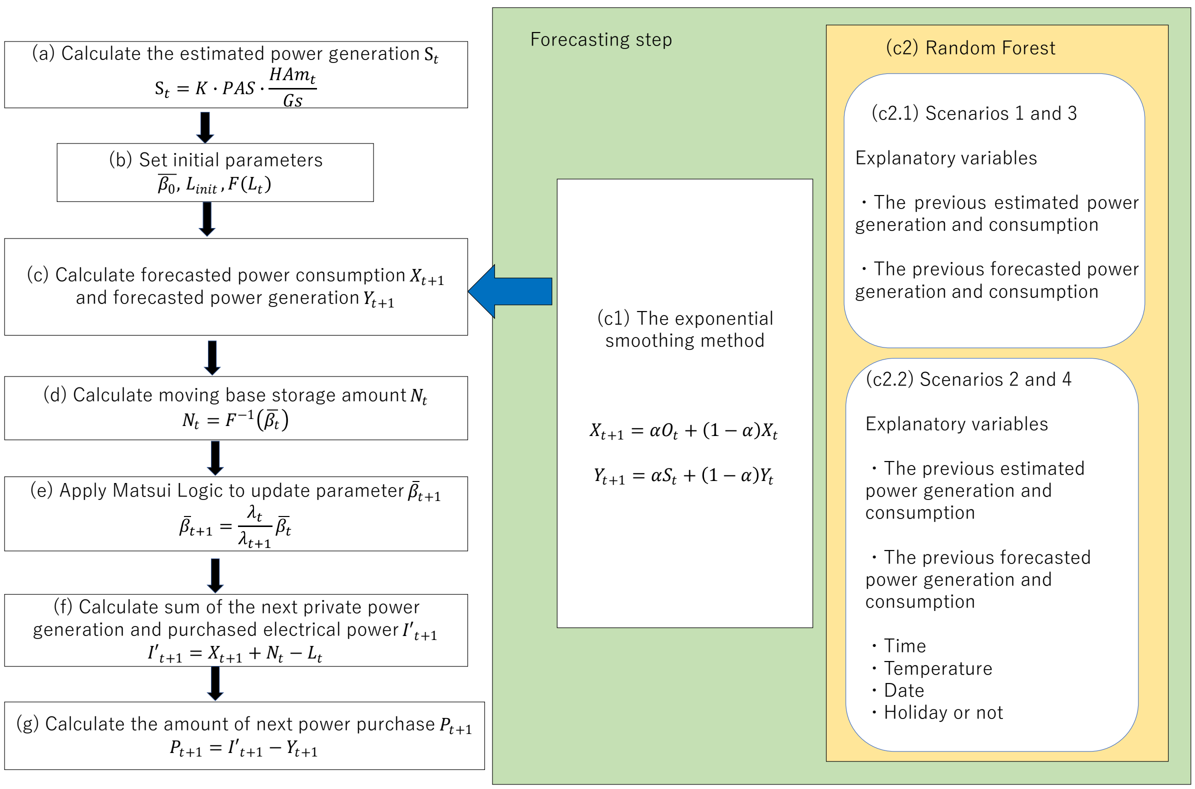

Figure 2. The procedure of applying the on-demand cumulative control method

3.3 Scenario of Explanatory Variables

In order to apply the random forest for forecasting power generation and consumption, the setting explanatory variables are needed. In this study, four combinations of explanatory variables are provided, “Scenario 1” to “Scenario 4”, respectively. Scenario 1 and Scenario 2 are used in the forecasting power generation, while Scenario 3 and Scenario 4 are used in the forecasting power consumption as shown in Table 2. In order to compare the difference of the forecasting method between exponential smoothing method and random forest, Scenarios 1 and 3, which are the same explanatory variables to the exponential smoothing method (Takada et al. 2024) are set in forecasting power generation and consumption, respectively. Moreover, Scenarios 2 and 4 added the another variables in order to investigate the effect of considering the characteristic of period and climate on forecasting power generation and consumption.

Table 2. The combination of setting explanatory variables

Scenarios	Target of the forecast	Explanatory variables
Scenario1	power generation	・The previous estimated power generation ・The precious forecasted generation
Scenario2	power generation	・The previous estimated power generation ・The previous forecasted generation ・Time ・Temperature ・Date ・Holiday or not
Scenario3	power consumption	・The previous power consumption ・The precious forecasted consumption
Scenario4	power consumption	・The previous power consumption ・The precious forecasted consumption ・Time ・Temperature ・Date ・Holiday or not

3.4 Scikit-learn

Scikit-learn is one of the Python library. It has several essential tools for machine learning such as classification and regression. Moreover, Scikit-learn includes effective tools for making the data analysis such as using NumPy, SciPy and Matplotlib convenient (Ledmaoui et al. 2023).

3.5 Random Forest

Random forest is a machine learning algorithm that collect many slightly different decision trees based on ensemble learning that called bagging. (Fan et al. 2022) It can be used for both classification and regression. The final prediction in random forest is made by correcting the result of predictions of all individual decision trees and averaging the results in regression tasks. The advantage of using random forest is its high forecasting precision and the ability to prevent overfitting by using many decision trees. In this study, 80% of the data from the beginning of the measurement period is used as training data and the rest is used as test data.

3.6 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is one of performance indicators to measure the error that shows the absolute difference between the value of source data and predicted data. It is defined as shown in equation (8). $\hat{d}$ shows the forecasted data and d_i shows the source data in period i (Ledmaoui et al. 2023).

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| d_i - \hat{d} \right| \tag{8}$$

4. Data Collection

4.1 Annual Power Generation and Consumption Data

In order to analyze the annual solar power generation and power consumption data, the annual power generation and consumption data are required for demand-to-supply management.

Table 3 shows an overview of power generation and consumption data at the distribution center in Yokohama, Japan. The distribution center treats food products. Moreover, the annual power consumption data were recorded hourly and provided by Ecolomy Co., Ltd. The annual solar power generation data are unknown. This is because the new solar power generation system was not installed yet in the measurement period of power consumption data. Therefore, the power generation data are estimated based on the volume of hourly solar radiation data, obtained from the New Energy and Industrial Technology Development Organization (NEDO 2021). It is assumed that the distribution center installed the 20kW photovoltaic panels. Moreover, the capacity of the storage battery is assumed 5kWh.

Table 3. Overview of estimated power generation and actual power consumption data

Data Attributes	This Study
Target facility	Distribution center in Yokohama, Japan
Measurement period	From March, 2020 to February, 2021
Measurement interval	One hour
Power generation data	Estimated based on actual solar radiation data provided by NEDO
Power consumption data	Actual data provided by Ecolomy Co., Ltd.
Power generation capacity of the photovoltaic panel	20kW
Capacity of storage battery	5kWh
Period of training data	80% of the data from the beginning of the measurement period and the rest for the test data

5. Results and Discussion

5.1 Comparison Between the Expanding Smoothing Method and Random Forest

This section indicates the comparison of random forest and exponential smoothing methods in terms of the precision of forecasting power generation and consumption. In applying the exponential smoothing method, Scenario 1 is used in forecasting power generation, and Scenario 3 is used in forecasting power consumption as the explanatory variables

5.1.1 Prediction Precision for Power Generation

This section shows the result of comparing random forest and exponential smoothing method in terms of the forecast precision for power generation in order to investigate the effect of applying random forest as shown in in Table 4. Table 4 shows the comparison between random forest and exponential smoothing method in terms of MAE in forecasting power generation when the same explanatory variables. The result shows that the value of MAE obtained from random forest was smaller than using the expanding smoothing method by 72%. On the other hand, it was considered that the previous estimated power generation is more important than the previous forecasted power generation when random forest and scenario 1 are used for forecasting power generation as shown in feature importance in Table 5.

Table 4. Comparison of the expanding smoothing method and random forest in terms of MAE in forecasting power generation

	The expanding smoothing method	Random Forest
MAE	1.32	0.37

Table 5. Comparison the expanding smoothing method and random forest in feature importance of power generation

Parameters	Feature importance
The previous estimated power generation	0.90
The previous forecasted power generation	0.09

5.1.2 Prediction Precision for Power Consumption

This section shows the result of comparing random forest and exponential smoothing method in terms of the forecast precision for power consumption in order to investigate the effect of applying random forest. Table 6 shows the comparison between the random forest and exponential smoothing method in terms of MAE in forecasting power consumption when the same explanatory variables. The result shows that the value of and MAE using random forest was 14% larger than using the expanding smoothing method. The factor of this result was considered that random forest regarded the previous actual power consumption is less important than the previous forecasted power generation as shown in feature importance in Table 7. Therefore, setting the previous forecasted power consumption as the explanatory variables and using random forest is considered to improve the precision in forecasting power consumption.

Table 6. Comparison the expanding smoothing method and RF in terms of MAE in forecasting power consumption

	The expanding smoothing method	Random Forest
MAE	1.76	2.06

Table 7. Comparison the expanding smoothing method and random forest in feature importance of power consumption

Parameters	Feature importance
The previous actual power consumption	0.77
The previous forecasted power consumption	0.23

5.2 Difference of Explanatory Variables in Random Forest

5.2.1 Difference of Explanatory Variables in Forecasting Power Generation when Using Random Forest

Section 5.1 showed the result of the difference between the random forest and exponential smoothing method under the same types of explanatory variables. The improvement of prediction precision for power generation and consumption prevents the expansion of error between forecasted data and actual data and penalty cost for additional power purchase or storage opportunity loss in demand-to-supply management. Therefore, this section shows the prediction precision of power generation. Additionally, Table 8 shows the comparison of different explanatory variables in terms of MAE in forecasting power generation. This result shows that using "Scenario 1" obtains only 5% higher precision for forecasting solar power generation than using "Scenario 2". The feature importance is estimated as the factor of this result. Table 9 shows the feature importance in the forecasting power generation. According to the feature importance, adding explanatory variables changed the feature importance of "the previous estimated power generation" by only 2.2%. Therefore, the previous estimated power generation has significant effect on the precision of forecasting power generation in that case.

Table 8. MAE forecasting power generation in random forest

	Explanatory variables	
	Scenario 1	Scenario 2
MAE	0.37	0.34

Table 9. Feature importance of forecasting power consumption in random forest

	Feature importance	
	Scenario 1	Scenario 2
The previous estimated power generation	0.90	0.88
The previous forecasted power generation	0.09	0.02
Time		0.09
Temperature		0.03
Date		0.06
Holiday or not		0.01

5.2.2 Difference of Explanatory Variables in Forecasting Power Consumption when Using Random Forest

This section shows the precision of forecasting power consumption. Table 10 shows the comparison of different explanatory variables in terms of MAE in forecasting power consumption. This result shows that using "Scenario 3" obtains 29.6% higher precision for forecasting solar power consumption than using “Scenario 4”. The feature importances are estimated as the factor of this result. Table 11 shows the feature importances in the forecasting power consumption. According to the feature importances, adding explanatory variables changed the feature importance of “the previous actual power consumption” by only 2.6% as shown in Table 11. Therefore, the previous estimated power consumption has significant effect on the precision of forecasting power consumption.

Table 10. MAE forecasting power consumption

	Explanatory variables	
	Scenario 3	Scenario 4
MAE	2.06	1.45

Table 11. Feature importance of power generation

	Feature importance	
	Scenario 3	Scenario 4
The previous actual power consumption	0.77	0.75
The previous forecasted power consumption	0.23	0.06
Time		0.09
Temperature		0.02
Date		0.06
Holiday or not		0.01

5.3 Hourly Power Generation and Consumption

Sections 5.1 and 5.2 show the prediction precision for power generation and consumption annually. On the other hand, this section shows hourly estimated power generation and actual consumption data and forecasted one in order to investigate the hourly features of forecasting solar power generation and consumption at the target facility. Figures 3 and 4 show the comparison about the average of hourly source and forecasted power generation data. They are found that using random forest are able to follow the hourly variation more closely than using the exponential smoothing method when forecasting both power generation and consumption.

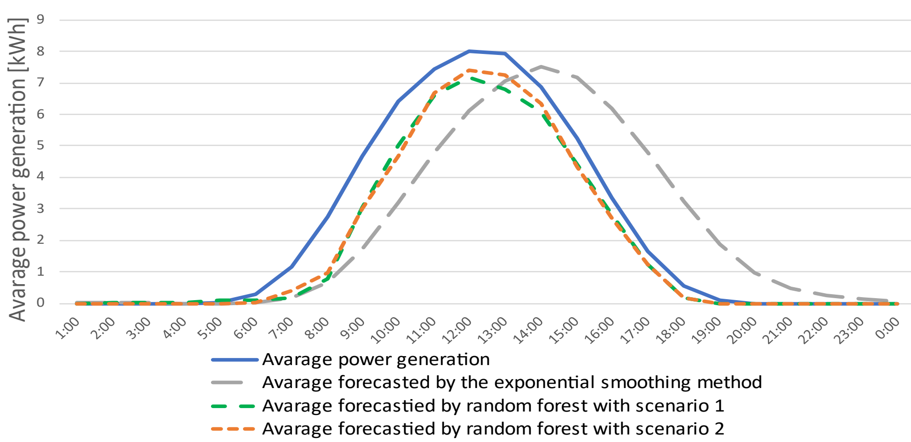

Figure 3. The average of hourly source and forecasted power generation

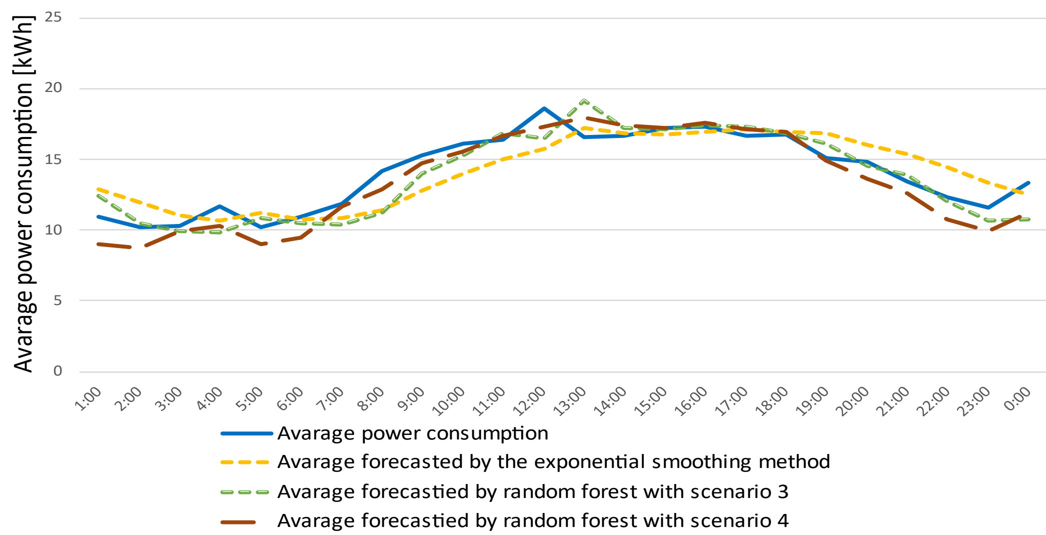

Figure 4. The average of hourly source and forecasted power consumption

5.4 Total Power Purchase Amount

This section investigates the difference when different forecasting methods are applied to demand-to-supply management. Figure 5 shows the comparison of total power purchase amount. It indicates that using random forest for forecasting is 7.3% higher than using the exponential smoothing method. This result showed that the total power purchase amount is more 7.1% larger when using random forest in scenario 1 and 3 than using the exponential smoothing method. It shows that, the improvement of forecasting precision does not lead to the decrease in the total power purchase amount. Therefore, the forecasting method should choose the appropriate option depending on the situation. If the forecasting precision want to be improved, random forest should be used. While the total power purchase amount wants to be reduced, exponential smoothing method should be used.

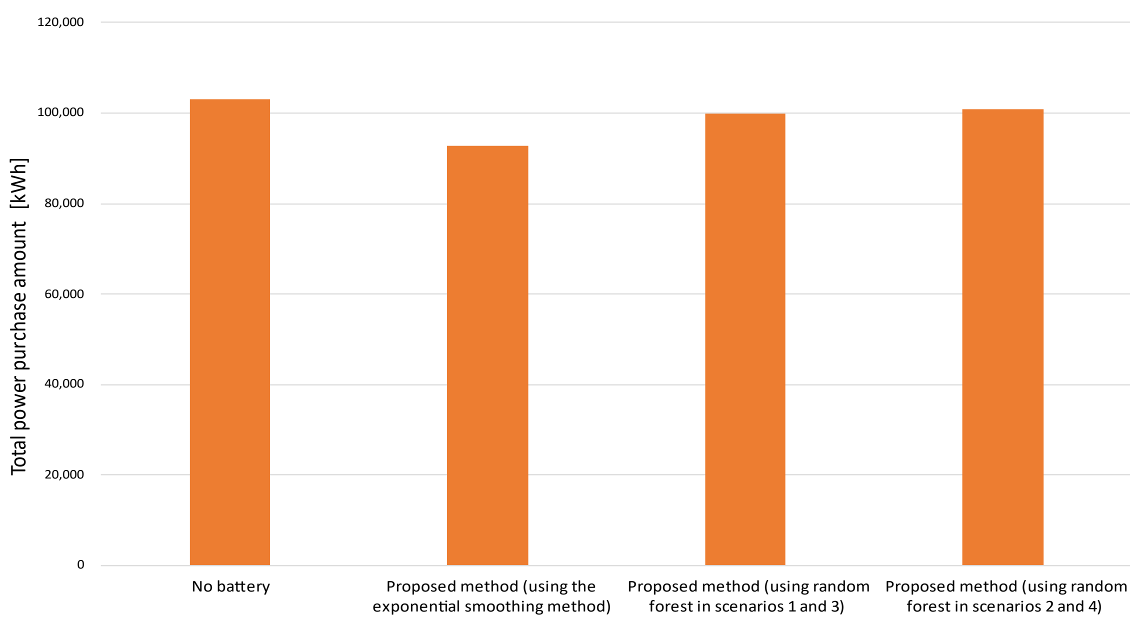

Figure 5. Comparison of total power purchase amount

6. Conclusion

This study analyzed the effect of the difference of forecasting method between the exponential smoothing method and random forest in the case of applying solar energy demand-to-supply management at the distribution center. The results showed that using random forest could be higher precision for forecasting power generation and consumption than using the exponential smoothing method. However, applying random forest made the total power purchase amount higher than using the exponential smoothing method. Therefore, the improvement of the precision for forecasting power generation and consumption does not necessarily mean that the total power purchase amount will decrease.

For future study, the implementing quantitative evaluation of GHG emission when the proposed method is applied to the solar energy demand-to-supply management is involved. This is because, considering GHG emission are helpful for developing more eco-friendly demand-to-supply management.

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