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Solar Energy Demand-to-Supply Management by the On-Demand Cumulative-Control Method: Case of a Childcare Facility in Tokyo

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Abstract: In recent years, environmental and energy issues relating to global warming have become more serious, and there is a need to shift from conventional power generation, which emits an abundance of carbon dioxide, to renewable energy sources without emissions, such as solar and wind. However, solar power generation, which is one of the renewable energies, changes dynamically, depending on real time weather conditions. Thus, power supplied mainly by solar power generation is often unstable, and an appropriate on-demand energy management for demand-to-supply is required to ensure a stable power supply. Demand-to-supply management methods include inventory management analysis and on-demand inventory management analysis. The cumulative-control method has been used as one of the production management methods to visually manage inventory status in factories and warehouses, while the on-demand cumulative-control method is an extension of inventory management analysis. This study models a demand-to-supply management method for a solar power generation system by using the on-demand cumulative-control method in an actual case. First, a demand-to-supply management method is modeled by an on-demand cumulative-control method, using actual power data from a childcare facility in Tokyo. Next, the on-demand cumulative-control method is adopted to the case without batteries, and the amount of electricity to be purchased is estimated. Finally, the effectiveness of the maximum battery capacity and the amount of the initial charge are examined and discussed by sensitivity analysis.

Keywords: renewable energy; electricity storage management; power demand and supply forecast; initial charge; dynamic inventory control

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1. Introduction

In recent years, global warming has become increasingly serious. The 26th session of the Conference of the Parties to the United Nations Framework Convention on Climate Change (COP26) was held in Glasgow, where more than 130 leaders showed an effort to counter global climate change (UNFCCC) [1]. U.S. President Joe Biden set a 50–52% reduction target for GHG emissions by 2030 at the climate summit [2]. According to BBC news [2], Japan has the fifth largest greenhouse gas (GHG) emissions in the world. The Japanese Prime Minister, Yoshihide Suga, has established a plan for a carbon-free society, aiming to reduce greenhouse gas emissions to zero by 2050 [3]. Encouraging the decarbonization of the energy industry is essential to achieving this aim, as this industry contributes a substantial fraction of global carbon dioxide emissions, a major greenhouse gas. Thus, the Ministry of the Environment (2020) [4] in Japan has also demanded more effective measures for the entire energy sector. The introduction of carbon-free renewable power generation (e.g., solar and wind) is also being actively implemented [3,5,6].

Solar power is dependent on sunlight; therefore, it has been stated that, provided the sun is present, solar power resource depletion should not be of concern. While many manufacturing companies and service organizations are beginning to use solar power for factory and facility operations, achieving stable solar power generation has been problematic. This is because solar power is weather dependent, making it difficult to balance supply and demand [7]. Thus, batteries and power purchasing from electric power companies are often used to meet the gap between energy demand and supply. Figure 1 shows a renewable energy system based on the relationship among supply, demand, and inventory. In supply, private power generation from solar power and power purchased from electrical companies are inflow to a battery. The outflows from the battery are connected to a demand facility as the power consumption in the facility. There are energy transition issues for solar power demand-to-supply as follows: When should we switch power purchasing to private power generation or private power generation to power purchasing? Additionally, how much energy should we store in batteries at each moment?

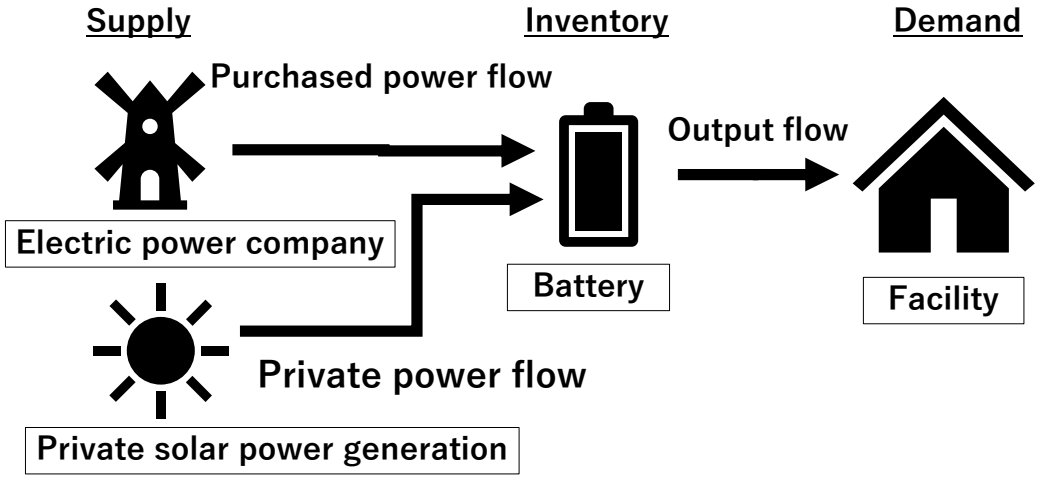


Figure 1. A renewable energy system based on the relationship among supply, demand, and inventory.

Regarding renewable energy for hardware and mechanism improvement, Agyekum et al. (2021) experimentally investigated actual solar power generation [8–10] and emulated the wave energy [11]. Agyekum et al. (2021) [8] aimed to be a lower temperature of the solar photovoltaics (PV) through double-sided water cooling to increase power generation efficiency. However, they did not focus on the power consumption. Agyekum et al. (2021) [9] investigated the effect of a combination of active and passive cooling mechanisms for the solar PV module. They combined aluminum fins, water, and ultrasonic humidifier to cool solar PV panels under real weather conditions. However, they did not mention the balance of solar power generation between supply and demand. Agyekum et al. (2021) [10] conducted an experiment on the performance enhancement of a solar PV from exergy, energy, and economy. They improved the performance by the cooling of a PV panel though they did not mention the balance of solar power generation between supply and demand. Agyekum et al. (2021) [11] proposed a test bench device to emulate a wave energy converter. They developed a prototype of a wave energy converter. Nevertheless, they did not compare the actual data to the simulation data. Furthermore, PraveenKumar et al. (2021) [12] conducted an experiment effectively for the passive cooling mechanism on the temperature change inside the solar cell and power generation performance. They prevented the solar cell's temperature from heating up, and they improved its performance by using this cooling mechanism. However, they did not consider the opportunity loss of energy storage due to full charging.

From the viewpoint of production research, this uncertain balance requires highly accurate demand forecasting and robust supply planning; this is also referred to as the demand-to-supply management method (DSMM) [13,14]. They used a cumulative control

method [15], which has long been used in process management and production planning for the intuitive quantification of the subsequent production amount. That production amount was based on the expression of the cumulative amount and the on-demand cumulative-control method (OCCM) [14]; this is the development method of DSMM.

Table 1 shows a literature review on renewable energy. In the research on energy demand-to-supply management, Wichmann et al. (2019) [16] approached the energy-oriented general lot-sizing and scheduling problems by combining them with decisions on utilizing energy storage for a single machine shop. They modeled production planning to minimize total costs related to production and energy, accommodating for energy trading. Moon and Park (2013) [17] attempted to minimize the total production cost with energy management by the flexible job-shop scheduling problem. However, their models did not include renewable energy management such as wind and solar. Uhlemair et al. (2014) [18] investigated capacity planning for a biogas plant and the course of the district heating network in Germany bioenergy villages. They generated a linear model to economically optimize the production and distribution systems of bioenergy villages. The sole power supply to their model was the biogas plant; as such, they did not consider procurement from other power generation companies, such as lignite power generation or natural gas.

Power generation from renewable energies such as solar has multiple issues. One of them is supply uncertainty because renewable energy generation is greatly affected by the weather. In order to overcome the supply uncertainty, there are three main approaches as follows: introducing a battery to store electricity; forecasting supply and demand; and using a stochastic model.

In terms of renewable energy with batteries, Trappey et al. (2013) [19] developed a hierarchical cost learning model for wind energy. Although the model had an improved fit between a hierarchical model and actual data, power supply and demand management were not considered. Pham et al. (2019) [20] developed a multi-site production and micro-grid planning model for net-zero energy operations. This approach was a two-stage optimization programming, such as the scheduling of production for electricity demand. In addition, the sizing and sitting of the microgrid systems were optimized. However, the study did not forecast supply and demand related to renewable power generation and consumption using an actual facility.

Regarding forecasting, Jahanpour et al. (2016) [21] proposed a collaborative platform for communities in the energy distribution network. This collaborative platform addressed the stochastic nature of electricity demand, the dynamics in power generation over time, and uncertainty through collaboration between energy providers to build a sustainable energy distribution network. However, their management model did not include energy supply from a battery. Rentizelas et al. (2012) [22] formulated the national electricity generation system in Greece. They analyzed and applied an optimization method to determine the optimal generating mix that minimized generation costs, while operating within system constraints and incorporating the uncertainty of emission allowance prices. However, their model operated using only annual energy supply and demand management, and they did not address daily supply and demand.

With respect to a stochastic model, Xydis (2013) [23] analyzed wind resources on Kythira Island, proposing an evaluation methodology and an investment tool. They estimated the wind resources and costs using the probability density function and cumulative distribution for variation in wind velocity. Furthermore, they proposed planning wind farms on Kythira Island. However, their model did not consider energy demand. Takanokura et al. (2014) [24] proposed energy management using a newsboy problem via storage systems for smart cities; however, their study did not account for demand-to-supply management using actual power generation. Santana-Vieraa et al. (2015) [25] proposed the implementation of a demand response program in large manufacturing facilities featuring distributed wind and solar energy using a stochastic programming model. The model allowed the manufacturer to meet curtailment requirements without causing major electricity

shortages that could adversely affect the normal production schedule. However, they did not deal with the change of supply and demand for each time zone.

Therefore, the proposed model in this study only consider the above three main methods: battery, forecasting, and a stochastic model. Thus, the originality and the novelty of this paper are finding that solar energy management issues have a similar structure with production management in overcoming uncertainty, and that the on-demand DSMM and OCCM methods can be applied to a solar power generation system. Furthermore, we demonstrated that both methods were applicable to the case of solar power generation system. One of the advantages of this method was that it enabled us to predict and to decide the amount of electricity to be purchased in the next period by changing storage capacity in real time in accordance with the amount of electricity consumed by using DSMM.

This study applies DSMM [13,26] to a solar power generation system associated with a renewable energy consulting company in Japan, Ecolomy Co., Ltd. (Tokyo, Japan) [27]. The total amount of generated renewable energy and purchased power is set as the input flow, the total power consumption is considered the output flow, and the remaining battery storage capacity is the inventory amount. These values are utilized as a case study for the demand-to-supply management of renewable power generation using data from private power generation and the power consumption grid in an actual childcare facility in Tokyo, Japan. This paper demonstrates that power demands could be met using a storage battery if solar power was unable to generate power. After that, the battery capacity and the storage required for the optimal operation of the solar system could be determined using on-demand and demand-to-supply management methods as it applied to actual childcare facility cases. Thus, the following research questions (RQs) were posed:

RQ1 What are the managerial issues including capital investment in a transition to solar power generation in the targeted renewable energy company?
RQ2 How was the demand-to-supply balance between the amount of electricity consumption and the amount of on-site solar power generation at the target facility?
RQ3 How to operate a battery more effectively by applying a demand-to-supply management developed in production and logistics? Additionally, how was the moving base storage capacity for on-demand DSMM?
RQ4 What was the effect of the day of the week, time of day, and weather on the demand-to-supply management in solar-power generation at the target facility?
RQ5 How effective are the capacity of the battery and the initial storage in the battery? Moreover, what is the energy storage opportunity loss at that time?

The remainder of this manuscript has been structured into four sections. Section 2 describes the model and the formulation of DSMM using the Cumulative-Control Method and OCCM. Section 3 presents the results of DSMM using the Cumulative-Control Method and OCCM, respectively. Section 4 conducts a sensitivity analysis for power storage capacity and initial storage to know the effects of designed storage capacities, obtains feedback from a partner renewable energy company, and discusses the results of the RQs. Finally, Section 5 concludes this study and develops future works.

Table 1. Literature review on renewable energy.

	Type of Renewable Energy				Demand-to-Supply		Overcoming Uncertainties				
	Solar	**Wind**	**Bio-Gas**	**Biomass**	**Supply**	**Demand**	**Battery Capacity**	**Stochastic Model**	**Forecast-ing**	**Real Data**	**Methods**
Wichmann et al. (2019) [16]						√					Energy-oriented lot-sizing and scheduling
Moon and Park (2013) [17]					√	√	√				Mixed integer programming
Trappey et al. (2013) [19]		√					√		√	√	Hierarchical learning model
Xydis (2013) [23]		√			√			√		√	Weibull and Rayleigh probability density function
Jahanpour et al. (2016) [21]		√			√	√		√	√	√	Trigonometric regression model
Santana-Vieraa et al. (2015) [25]	√	√			√	√		√		√	Stochastic programming
Takanokura et al. (2014) [24]	√				√	√	√	√	√		Newsboy problem
Pham et al. (2019) [20]	√	√			√	√	√	√			Stochastic planning model
Uhlemair et al. (2014) [18]			√		√	√				√	Mixed integer linear programming
Rentizelas et al. (2012) [22]	√	√		√	√	√		√	√	√	Forward-sweeping linear programming
This study	√				√	√	√	√	√	√	On-demand cumulative-control method

2. Methods

In order to apply the DSMM to renewable energy, Section 2 describes the model and the formulation of DSMM, using the cumulative-control method and OCCM. Section 2.1 shows the procedure performed for the demand-to-supply management analysis of renewable power generation. Section 2.2 models a DSMM for renewable energy. The cumulative-control method is explained in Section 2.3. In Section 2.4, the on-demand DSMM model is applied to solar power generation.

2.1. Procedure

Figure 2 shows the procedure performed for the demand-to-supply management analysis of renewable power generation. The notations used in this study are shown in Table A1 in Appendix A.

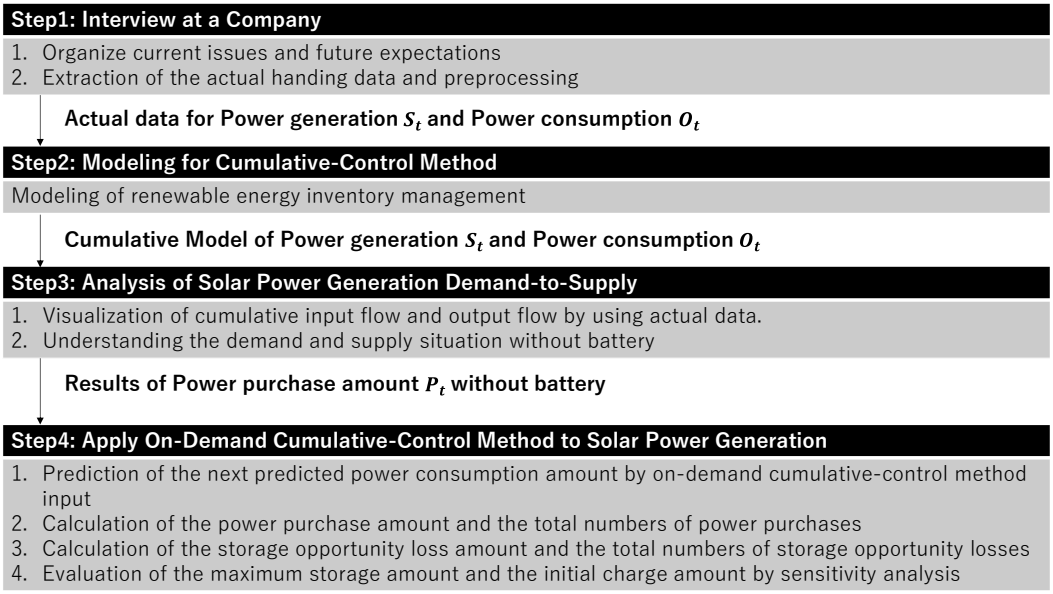


Figure 2. The procedure for the demand-to-supply management analysis of renewable power generation.

In Step 1, interviews are conducted with Ecolomy Co., Ltd., which operates a renewable energy-related business, to identify current issues and future expectations for the analysis when the actual data is examined. In Step 2, the DSMM model is applied to actual private power generation and consumption data.

In Step 3, the cumulative inflow and outflow are visualized using actual data and confirmed for the demand-to-supply situation in a case without a storage battery. In Step 4, the on-demand DSMM [26] is applied to the model created in Step 2. Specifically, the next forecasted power consumption amount X_{t+1} is determined, and the moving base storage capacity N_t is obtained. Moreover, the next power purchase amount P_{t+1} after the parameter $\overline{\beta}_{t+1}$ is updated using Matsui logic [13]. The inventory distribution $F(L_t)$ used in the N_t calculation is derived from actual storage data. Furthermore, the next power purchase amount P_{t+1} and the total numbers of power purchases TP_{count} are determined. The storage opportunity loss amount L_{loss_t} and the total numbers of storage opportunity losses TL_{count} are then calculated to evaluate the initial storage capacity L_{init} and the maximum storage capacity L_{max} of the storage battery by sensitivity analysis.

2.2. DSMM Model

Figure 3 shows a DSMM for renewable energy based on the relationship among supply, demand, and inventory. In this study, the DSMM is applied using the remaining level of the storage battery as the inventory; the time until the stored electrical power is released is regarded as the lead time; the amount of private power generation and power purchased

from electrical companies is the inflow, so that the sum of this electric power over time period t is set as the inflow amount I_t. The outflow amount O_t is used as the power consumption of the facility, the maximum storage capacity of the battery is L_{max}, which means the warehouse capacity in the production system, and the initial charge amount is L_{init}, which corresponds to the initial inventory amount in the production system.

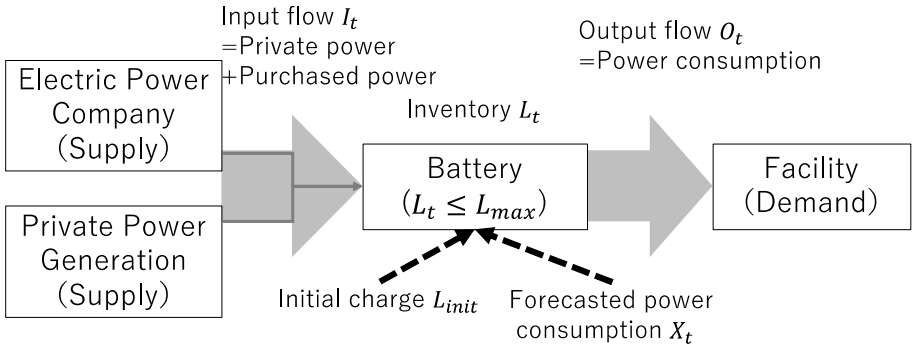


Figure 3. Demand-to-supply management model for renewable energy.

2.3. Cumulative-Control Method

The relationship among supply, demand, and inventory is modeled to apply the DSMM to the amount of private energy generation and consumption obtained from the actual facility. The DSMM is often used in process and progress management for the quantitative analysis of work and inventory [13]. The supply chain refers to the products in progress or inventory of the process.

In the DSMM, cumulative input and output are plotted on a two-dimensional graph, with the period and the quantity set as the horizontal and vertical axes, respectively. The difference values in the vertical represents the numbers of flows, and that in the horizontal means the lead time.

2.4. Application of On-Demand DSMM to Solar Power Generation

The cumulative inflow and outflow are obtained from the recorded data to grasp the demand-to-supply situation for solar power generation without storage batteries. Cumulative inflow refers to the total amount of private power generation corresponding to the amount of electrical power from solar power generation in the facility at period t, S_t. Cumulative outflow refers to the total amount of power consumption corresponding to the amount of power consumption in the facility at period t, O_t.

Further, the cumulative power purchase amount is determined to understand the demand-to-supply situation when no storage batteries are present. The power purchase amount at period t is represented as $P_t = \max(0, O_t - S_t)$. This means the amount of electricity purchased from electric power companies when the private power generation is insufficient.

Unlike the conventional DSMM, the on-demand DSMM [26] changes the base supply in response to the reconfiguration of demand structure. Thus, it enables on-demand changes in the next input amount. The procedure for applying the on-demand DSMM is shown in Figure 4.

In Step (a), the following parameters were set to their initial values: coefficient α $(0 \leq \alpha \leq 1)$ used in the exponential smoothing method, the initial value $\overline{\beta}_0$ $(0 \leq \overline{\beta}_0 \leq 1)$ of the input amount determination parameter updated by Matsui logic, the cumulative probability distribution $F(L_t)$ for the frequency of the remaining storage capacity, the initial storage capacity L_{init} $(0 \leq L_{init} \leq L_{max})$, and the maximum storage capacity L_{max} $(0 \leq L_{max})$.

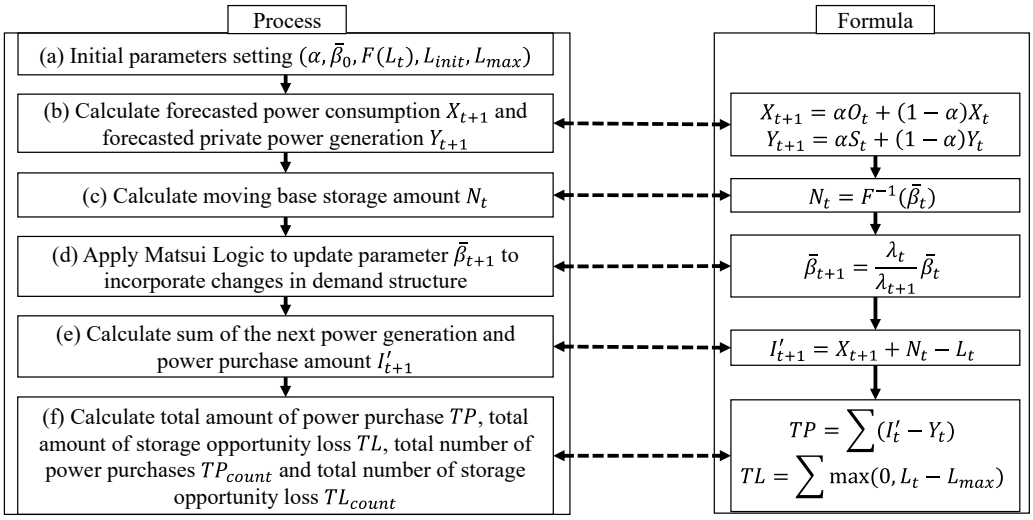


Figure 4. Procedure for applying the on-demand DSMM to renewable power generation.

In Step (b), the amounts of forecasted power consumption X_{t+1} and forecasted private power generation Y_{t+1}. were calculated using the exponential smoothing method [28] using Equations (1) and (2). The storage opportunity loss amount L_{loss_t} was determined using the forecasted power consumption amount, the next input amount I'_t, and the forecasted private power generation.

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

$$Y_{t+1} = \alpha S_t + (1-\alpha)Y_t \quad (2)$$

In Step (c), the moving base storage capacity N_t was calculated. Insufficient inventory could lead to out-of-stock losses, whereas excess inventory could lead to capacity pressure and increased storage costs, so an appropriately sized inventory is desirable. To that end, Matsui et al. (2005) [26] used the newsvendor problem to determine the base supply chain that minimized costs due to excess inventory or insufficient stock. In this study, the newsvendor problem was used to calculate N_t.

The calculation of N_t required solving the newsvendor problem of cost minimization, expressed by the total cost function $C(N_t)$ in Equation (3):

$$C(N_t) = \beta_1 N_t + \beta_2 (N_t - L_t)^+ + \beta_3 (L_t - N_t)^+ \quad (3)$$

Here, L_t is the remaining storage capacity in period t, β_1 is the cost coefficient of maintaining storage, β_2 is the cost coefficient of insufficient storage, β_3 is the cost coefficient of excess storage [26], and $(a)^+ = max(a, 0)$. At this time, the solution N_t is equal to L_t, which satisfies Equation (4) using the cumulative probability distribution $F(L_t)$ of the frequency of stored electricity.

$$F(L_t) = \overline{\beta}_t \quad (4)$$

where $\overline{\beta}_t$ is determined by Equation (5), which consists only of the cost coefficients β_1, β_2, and β_3.

$$\overline{\beta}_t = \frac{\beta_3 - \beta_1}{\beta_2 + \beta_3} \quad (5)$$

However, $\overline{\beta}_t$ cannot be updated in the calculation of Equation (5), and thus, cannot follow fluctuations in demand. In the on-demand DSMM, $\overline{\beta}_t$ is updated every period according to the demand fluctuations using Matsui logic [13] described in Step (d).

Figure 5 shows the calculation procedure for the cumulative probability distribution $F(L_t)$ of the remaining storage capacity L_t and the moving base inventory N_t.

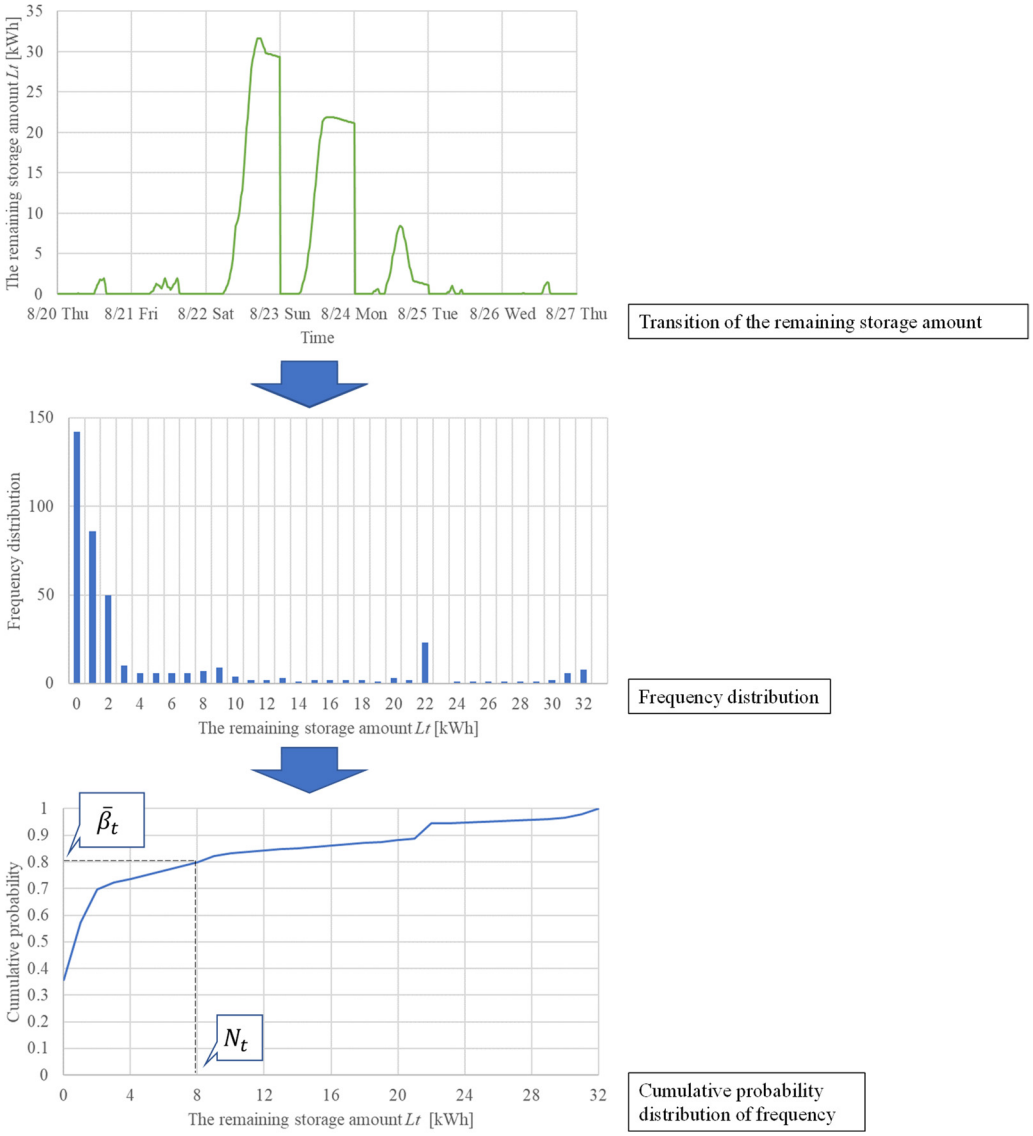


Figure 5. The calculation procedure for the cumulative probability distribution $F(L_t)$ with the remaining storage capacity L_t and the moving base inventory N_t.

The data period was limited to create the frequency distribution of L_t to obtain the cumulative probability distribution $F(L_t)$. Subsequently, the cumulative probability was derived from $F(L_t)$ and converted into a cumulative probability distribution. The cumulative probability distribution $F(L_t)$ of the remaining storage capacity L_t was determined, and the intersection between $F(L_t)$ and $\overline{\beta_t}$ was used to obtain the moving base inventory N_t.

In this study, six types of $F(L_t)$ were created: five from the electricity storage data from 5:00–19:00 on weekdays (20 August, 21 August, 24 August, 25 August, and 26 August) and one created from all electricity storage data from the period of 5:00–19:00.

In Step (d), $\overline{\beta}_t$ was updated using Matsui logic. Matsui et al. (2005) [26] updated parameters to incorporate changes in demand structure, adjust the base inventory to the momentary demand, and determine the subsequent input amount to maintain the corresponding base inventory. It was assumed that the parameter $\overline{\beta}_t$ over period t expressed in Equation (5) canceled the changes with the demand ratio λ_t shown in Equation (6):

$$\lambda_{t+1}\,\overline{\beta}_{t+1} = \lambda_t\,\overline{\beta}_t = \cdots = \lambda_0\,\overline{\beta}_0 \tag{6}$$

Equation (7) is modified from Equation (6) to obtain the next-period parameter $\overline{\beta}_{t+1}$, known as the Matsui logic parameter (Matsui et al., 2009) [13].

$$\overline{\beta}_{t+1} = \frac{\lambda_t}{\lambda_{t+1}}\overline{\beta}_t \tag{7}$$

From this, if the initial value of $\overline{\beta}_0$ is given, the cost for the next period will be updated continuously in response to fluctuations in demand, and the moving base storage capacity N_t can be calculated.

Here, the demand λ_t and forecasted demand λ_{t+1} were calculated using Equations (8) and (9), respectively.

$$\lambda_t = O_t \tag{8}$$

$$\lambda_{t+1} = X_{t+1} \tag{9}$$

For example, when $O_t = 10$, $X_{t+1} = 15$ and $\overline{\beta}_t = 0.3$, the parameters are updated, as expressed in Equation (10).

$$\overline{\beta}_{t+1} = \frac{\lambda_t}{\lambda_{t+1}}\overline{\beta}_t = \frac{O_t}{X_{t+1}}\overline{\beta_t} = \frac{10}{15} \times 0.3 = 0.2 \tag{10}$$

Furthermore, $\overline{\beta}_{t+1}$ must be $0 < \overline{\beta}_{t+1} \leq 1$ to calculate the base supply chain. Furthermore, the updates become more gradual as $\overline{\beta}_{t+1}$ approaches zero, and $\overline{\beta}_{t+1}$ does not move from around zero. Therefore, 0.1 was set to a lower limit of $\overline{\beta}_{t+1}$. Therefore, the parameter $\overline{\beta}_{t+1}$ was modified every time it was updated so that $0.1 < \overline{\beta}_{t+1} \leq 1$.

Finally, in Step (e), the next input amount I'_t to be input into the next period to bring the supply chain closer to the base supply chain, was calculated. This was the final output in the on-demand DSMM and the supply–chain management equation (Matsui et al., 2005 [26]; Equation (11)) was used.

$$I'_{t+1} = X_{t+1} + N_t - L_t \tag{11}$$

This next input amount I'_t must be controllable. Hence, in this study, the next power purchase amount P_{t+1} that was controllable in the inflow amount I_t was set as the next input amount I'_t. In Step (f), the next power purchase amount P_{t+1} was determined by Equation (12). A lower total sum $\sum P_{t+1}$ of P_{t+1} or total number of power purchases TP_{count} was thought to result in more favorable supply–demand management.

$$P_{t+1} = I'_{t+1} - Y_{t+1} \tag{12}$$

Furthermore, the storage opportunity loss amount L_{loss_t} when the opportunity to store electricity was lost due to a full charge was considered and determined by Equation (13). A lower total sum of storage opportunity loss $\sum L_{loss_t}$ or total number of storage opportunity losses TL_{count} was thought to result in more favorable supply–demand management.

$$L_{loss_t} = \max(0,\ L_t - L_{max}) \tag{13}$$

3. Results

Based on the procedure and model in Section 2, Section 3 demonstrates how to apply the proposed demand-to-supply management for renewable power generation to a case study. First, Section 3.1 organizes the company hearing from a company developing a renewable energy-related business named Ecolomy Co., Ltd. Next, the assumption of inflow and outflow for the power is explained in Section 3.2. Then, Section 3.3 analyzes demand-to-supply of solar power generation in a child care facility. Finally, the on-demand cumulative-control method is applied to solar power generation in Scenario 3.4.

3.1. Result of Step 1: Company Hearing

A hearing was conducted with Ecolomy Co., Ltd., [27], which is developing a renewable energy-related business, to discuss their current and future issues. The company was asked to provide the power consumption data of the facility that was operating both the solar and private power generation. After pre-processing, analyses using the DSMM were performed.

From the hearings with Ecolomy Co., Ltd., we were able to extract the following current issues: introduction costs are unrealistic if the storage battery has a large capacity; large variations are observed if one household attempts to make demand forecasts, leading to difficulty in achieving accurate predictions; attempts to accommodate electricity through a widespread power grid incur high transport charges so remote accommodation of electricity would be costly; and securing space for large-scale renewable energy power generation is difficult in Tokyo, a major electricity consumer.

We extracted opinions through the hearings, with the following particular exceptions: the proposal of a model that would require economical battery storage capacity, applications that would lead to a network of local production for intra-community consumption (i.e., microgrids), and the construction of a model that enabled stable power generation with other forms of renewable energy, such as wind and biomass.

In this study, we focused on a proposed model that could obtain an economically viable battery storage capacity and pursued this focus through the on-demand DSMM. Ecolomy Co., Ltd. provided private power generation and consumption data from actual solar power generation at a given facility. Three meetings with the company were held in October, November, and December 2020 to further understand the data.

Table 2 shows the details of the facility that provided the private power generation and consumption data. The facility was a children's daycare in Tokyo. The data during business hours for one week were obtained, with the target facility having a renewable power generator output of 10 [kW] in Tokyo.

Table 2. Source data on private power generation and consumption amount and their corresponding details.

Facility Attributes	Childcare Facility
Business hours	7:00–19:00 on weekdays and Saturdays
Data period	20 August–26 August in a given year
Panel power generation output	10 kW

Furthermore, power consumption from the facility was recorded as wattmeter log data at 15-min intervals, whereas the private power generation data were recorded as the total power generation amount per day. Hence, the time intervals needed to be arranged for analysis. First, the daily total of incoming solar radiation in Tokyo was obtained from Japan Meteorological Agency (2020) [29], and the total private power generation for one day was partitioned hourly with the corresponding fraction total solar radiation. Further, the hourly private power generation was divided by 1/4 to convert the data to 15-min intervals.

3.2. Result of Step 2: Modeling for Cumulative-Control Method

The variables used in the DSMM of renewable energy were implemented in this study. Private power generation, one of the components for the inflow amount I_t, which was pre-processed from daily private power generation data to 15-min increment data. The power consumption amount, which corresponds to the outflow amount O_t, required no further adjustment as the facility data provided by Ecolomy Co., Ltd. were wattmeter log data recorded every 15 min.

3.3. Result of Step 3: Analysis of Solar Power Generation Demand-to-Supply

Figure 6 shows a cumulative graph of observed power consumption, private power generation, and estimated power purchase amount for a given week in summer. It is assumed that there are no storage batteries. In this case, the cumulative power consumption amounts for a target period were 167.01 [kWh], and the cumulative private power generation was 153.24 [kWh], with a relatively slight difference of 13.77 [kWh].

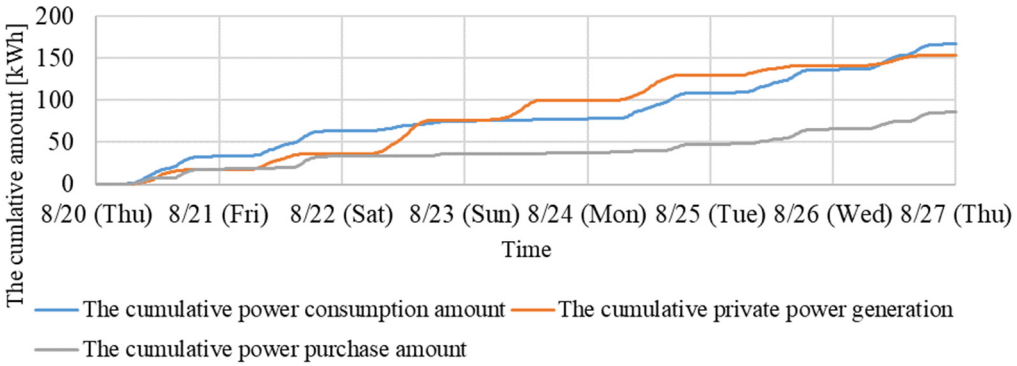


Figure 6. Cumulative graph displaying the amounts of observed power consumption and private power generation, and estimated power purchases across the time period analyzed.

Furthermore, the cumulative power purchase amount in 1 week was estimated as 85.83 [kWh], which corresponds to 51.4% of the cumulative power consumption. The total numbers of power purchases TP_{count} was 482, and the purchase of power occurred at a rate of 71.7% of the total measurement period, 672 periods. These results indicated that 72.06 [kWh] of electric power, 47.0% of the electric power generated by private power generation, was discarded without being used. Therefore, it turns out that such cases enabled us to reduce this cumulative power purchase amount by introducing a storage battery and more suitably managing demand-to-supply incompatibilities.

Moreover, cloudy and rainy weather meant that actual data were lower than the measured values of incoming solar radiation strength and duration. Therefore, potentially a further reduction for the cumulative power purchase amount would be expected.

3.4. Result of Step 4: Apply on-Demand Cumulative-Control Method to Solar Power Generation

The input data, including measurements, and output data of the model are related with the resulted main figures in Figure A1 in the Appendix A. The right-hand side of each equation in that figure is the input data, including the measurements, while left-hand side means the output data of the model.

In Step (a) the initial settings, five types of the cumulative probability distribution $F(L_t)$ of the remaining storage amount frequency were created from 5:00 to 19:00 on weekdays 20 August, 21 August, 24 August, 25 August, and 26 August 2020 and one from the total electricity storage data from the target period. Figure 7 shows the results for each $F(L_t)$. It is found that the maximum value of the remaining storage amount occurred on 24 August in Figure 7, as one of the best optimal weather conditions (e.g., sunshine hours, total insolation) were experienced on this day, and it allowed electricity storage to be increased for all the time. Furthermore, the frequency was widely distributed, and the cumulative probability distribution gradually rose. Therefore, the subsequent input amount could be determined.

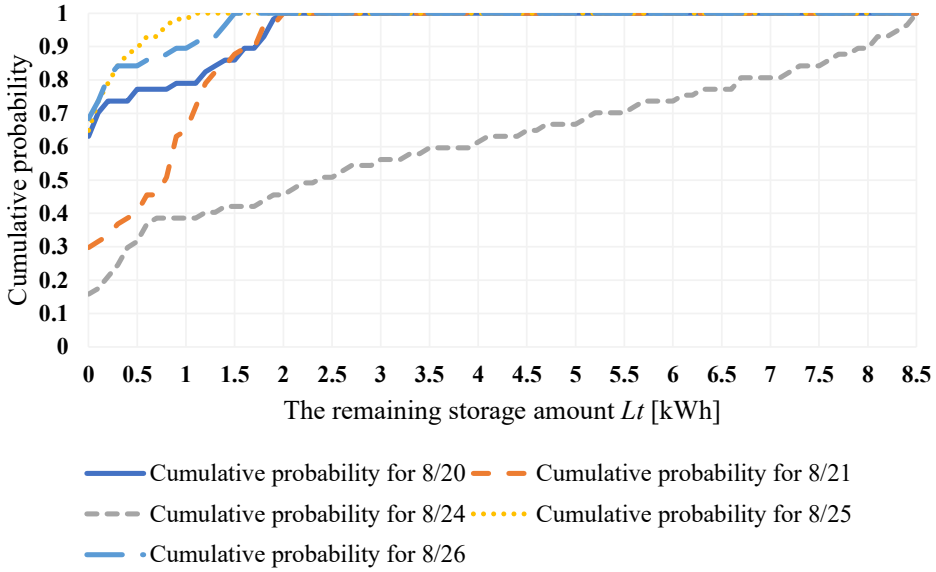
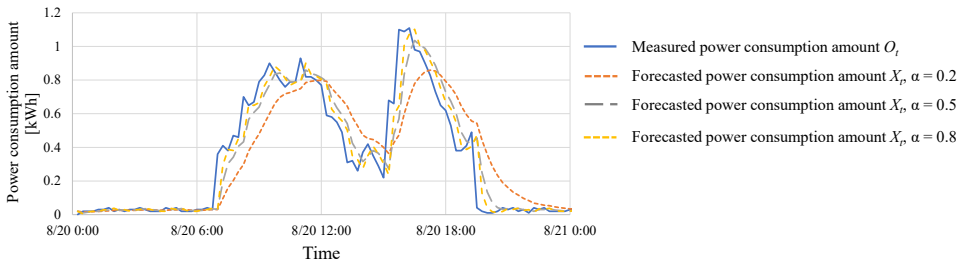
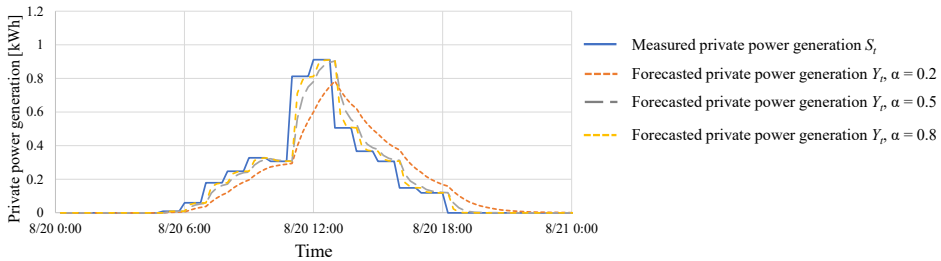


Figure 7. Cumulative probability distribution of the remaining storage amount from 20 August to 26 August.

In Step (b), forecasted power consumption X_{t+1} and forecasted private power generation Y_{t+1} on 20 August were calculated using the exponential smoothing method for each $\alpha = 0.2,\ 0.5,$ and 0.8, and the results are shown in Figure 8. The results indicate that accuracy increases with α. A large difference between the forecasted and the measured values is observed at $\alpha = 0.2$; however, making α too large increases the weight of the prior measured periods and results in the predicted values lagging behind.



(a) Forecasted power consumption X_t



(b) Forecasted private power generation Y_t

Figure 8. Predicted vs. measured power consumption amount X_{t+1} power generation Y_{t+1} based on α values of 0.2, 0.5, and 0.8.

Based on the above analysis, all subsequent calculations will use the forecasted power consumption amount X_{t+1} and private power generation Y_{t+1} calculated with an α value of 0.5.

In Step (c), the moving base storage amount N_t was obtained. Figure 9 shows the storage amount L_t ($L_{init} = 0,\ L_{max} = 5$) controlled by the moving base storage amount, obtained from the cumulative probability distribution $F(L_t)$ of the remaining storage amount L_t on 25 August, which had poor weather with clouds and occasional rain. This

pattern was observed because $N_t = 0$ when an increase in storage amount was detected, making it possible to refrain from purchasing electric power, However, it was also found that management of N_t. was difficult on 24 August when private power generation was large due to favorable conditions and holidays (22 August and 23 August) when the power consumption was small.

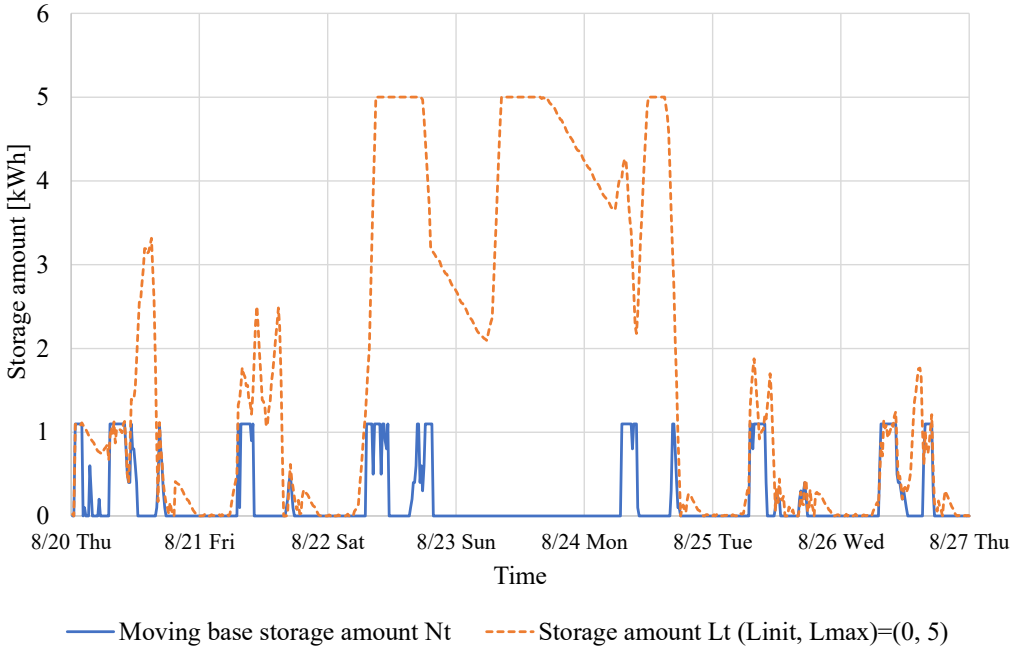


Figure 9. Moving base storage amount N_t and storage amount L_t ($L_{init} = 0$ kWh, $L_{max} = 5$ kWh) over the period analyzed.

Figure 10 shows the updated result of $\overline{\beta}_t$ due to Matsui logic when $\overline{\beta}_0 = 0$ (from step (d)). Further, $\overline{\beta}_t$ increased during the morning hours from 06:00 to 12:00 and in the hours around 16:00, with the exception of Sundays when the facility was closed. The possible reason is that these were the hours when the power consumption amount of the facility began to increase. Figure 11 shows shifts in the power consumption rates, which were often higher than the private power generation during these hours and are thus critical hours in terms of demand-to-supply management and the difference between private power generation and power consumption.

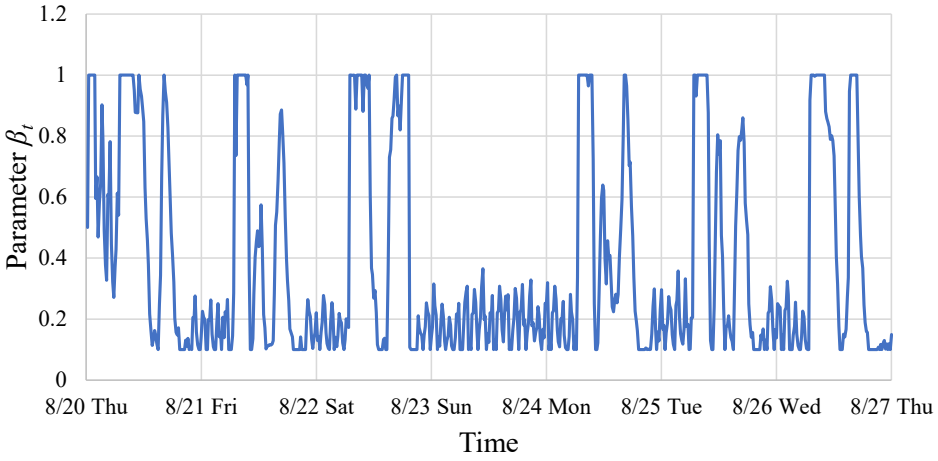


Figure 10. Updated result of $\overline{\beta}_t$ by Matsui logic ($\overline{\beta}_0 = 0.5$).

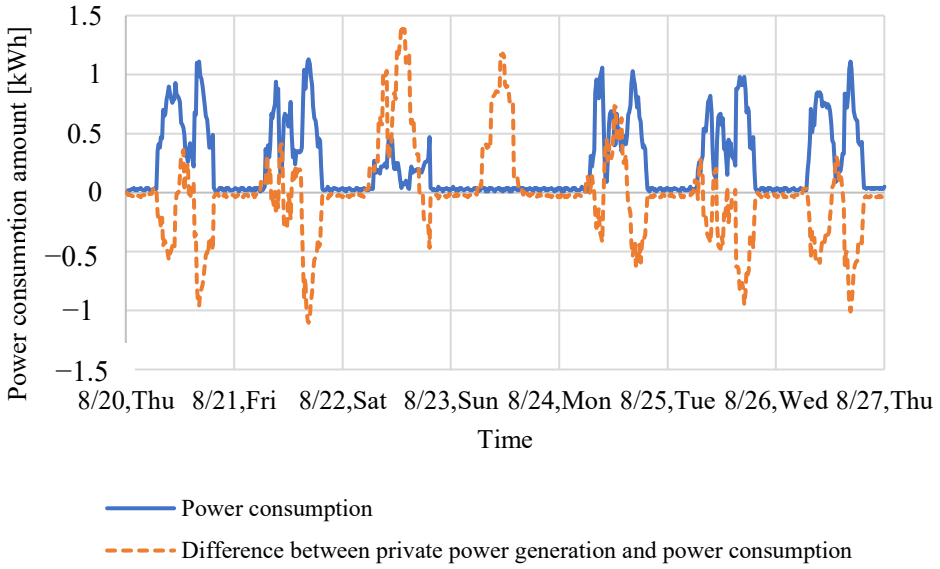


Figure 11. Power consumption and difference between private power generation and power consumption.

For all cumulative probability distributions $F(L_t)$, we conducted sensitivity analysis of the initial inventory amount L_{init} and the maximum storage amount L_{max} by evaluating the total power purchase amount TP, number of power purchases TP_{count}, storage opportunity loss amount TL, and the number of storage opportunity losses (TL_{count}, at Step (d)).

4. Impact of the Proposed Method

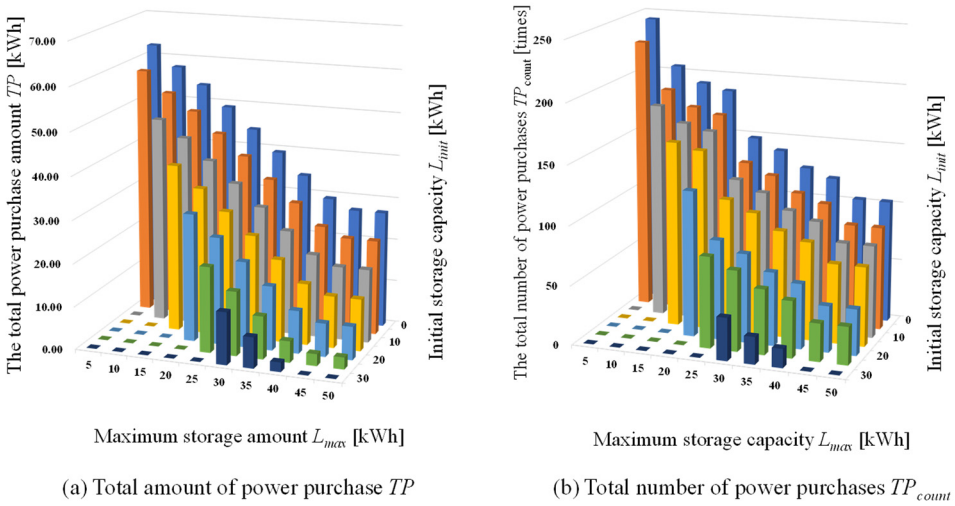
From Section 3, the solar energy at the facility surveyed was not used effectively because the timing of supply and demand was different. Therefore, it is desirable to introduce a storage battery to generate and store electricity. However, the larger capacity of the storage batteries brings a higher installation cost.

This section analyzes the impact of the proposed method in the designed system. In Section 4.1, sensitivity analysis is conducted for the initial inventory and maximum storage capacity, with the total power purchase amount, the total number of power purchase, and the amount of storage opportunity loss as evaluation targets. Section 4.2 receives feedback from Ecolomy Co., Ltd. about the results of Section 4 and evaluates the application of this study based on this feedback. Finally, Section 4.3 discusses answers of the RQs.

4.1. Maximum and Initial Storage Capacities by Sensitivity Analysis

A sensitivity analysis is carried out to assess the value of the maximum and initial storage capacity of the batteries.

Figure 12a shows the sensitivity analysis results of the total power purchase amount TP in the cumulative probability distribution $F(L_t)$ of the remaining storage amount L_t on 25 August. TP at this time was the smallest compared to the other cumulative probability distributions when the maximum storage amount $L_{max} = 45$ [kWh] and 50 [kWh] and the initial inventory amount $L_{init} = 30$ [kWh]; however, L_{init} needed to be purchased at $t = 0$. Furthermore, increases in L_{max} and L_{init} by 5 [kWh] each often resulted in a TP reduction by 5 [kWh] or less each time. Since TP can be difficult to be decreased, even by L_{max} or L_{init}, intentionally increasing these values should be avoided. If demand-to-supply management was performed with a $TP \leq 30$ [kWh], then combinations of $L_{max} = 40$ [kWh] and $L_{init} = 0$ [kWh], or $L_{max} = 20$ [kWh] and $L_{init} = 20$ [kWh] could be conceivable. Though the introduction costs of storage batteries are very high, it is demonstrated that a large initial inventory with a small battery was effective such as $L_{max} = 20$ [kWh] and $L_{init} = 20$ [kWh].



(a) Total amount of power purchase TP (b) Total number of power purchases TP_{count}

Figure 12. Sensitivity analysis for (**a**) total power purchase amount TP and (**b**) total number of power purchases count TP_{count}.

Figure 12b show the results of the sensitivity analysis of the total number of power purchases TP_{count}, with the cumulative probability distribution $F(L_t)$ of the frequency of the remaining storage amount L_t on 25 August.

These results indicate that the change in the total power purchase amount TP corresponded to the change in TP_{count}, but the TP did not always match the changes in TP_{count} when 5 [kWh] of change was observed. For example, changing from a maximum storage amount L_{max} from 25 to 30 [kWh], while maintaining initial inventory L_{init} at 15 [kWh], resulted in a decrease in TP_{count} by 9 [times]. Alternatively, changing L_{max} from 30 to 35 [kWh], while maintaining $L_{init} = 15$ [kWh], resulted in a decrease of TP_{count} by 13 [times]. The reason for this difference was likely because increasing L_{max} could bring more storage amount on Saturday and Sunday. Thus, decreasing the timing at which the storage decreased to and became zero and the power purchase occurred was slower when changing from 30 to 35 [kWh] than from 25 to 30 [kWh].

Furthermore, differences in the amount of change of L_{init} were observed depending on the difference in the periods of high power consumption from 20 to 21 August. Figure 13 shows the changes in the power purchase amount when $L_{max} = 10$ [kWh], and L_{init} values are 0, 5, or 10 [kWh]. The changes in the total power purchase capacity TP_{count} is also added. It was shown that unifying the amount of change in the power purchase amount was difficult as some factors, such as power consumption amount and private power generation, are difficult to control as constant.

Figure 14a shows the results of the sensitivity analysis for the total storage opportunity loss amount TL when a cumulative probability distribution $F(L_t)$ of the remaining storage amount L_t on 25 August was used. TL reached its minimum during this period, when compared to the other cumulative probability distributions.

There were no changes due to the initial inventory amount L_{init} when $L_{init} \leq 25$ kWh, and changes in the maximum storage amount L_{max} resulted in decreases of the storage opportunity loss amount by the same amount. However, TL increased at $L_{init} = 30$ [kWh] compared to the range of the initial inventory amount $L_{init} \leq 25$ [kWh] because battery consumption peaked at 27.9 [kWh] on 22 August when the weather was poor, as shown in Table A2 in Appendix A [29]. As a result, L_{init} was not entirely consumed by 22 August, and the battery was fully charged at a faster rate than in $L_{init} \leq 25$ [kWh], when the weather improved and consumption decreased. Further, $L_{init} \geq 30$ [kWh] was unfavorable when conducting demand-to-supply management from Thursday. It could also be observed that L_{init} could be decreased as the starting date of demand-to-supply management approached the day when power consumption decreased and private power generation was high.

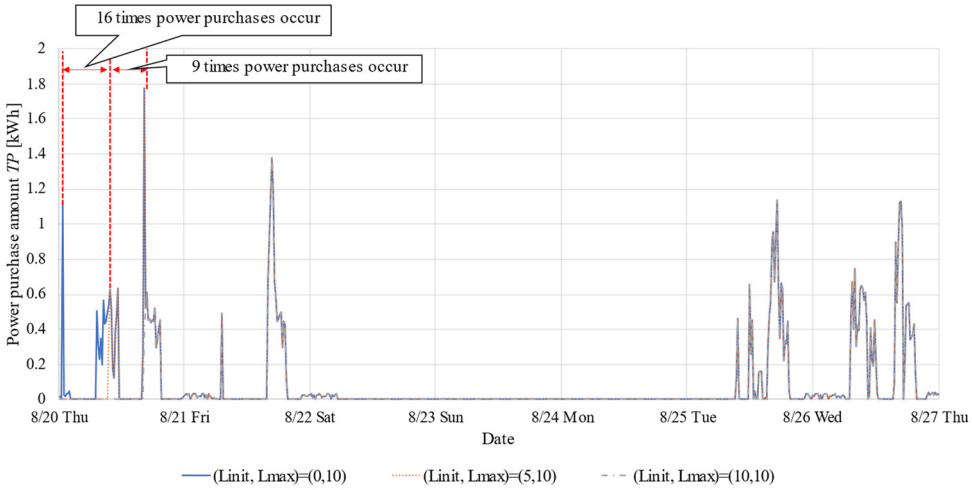
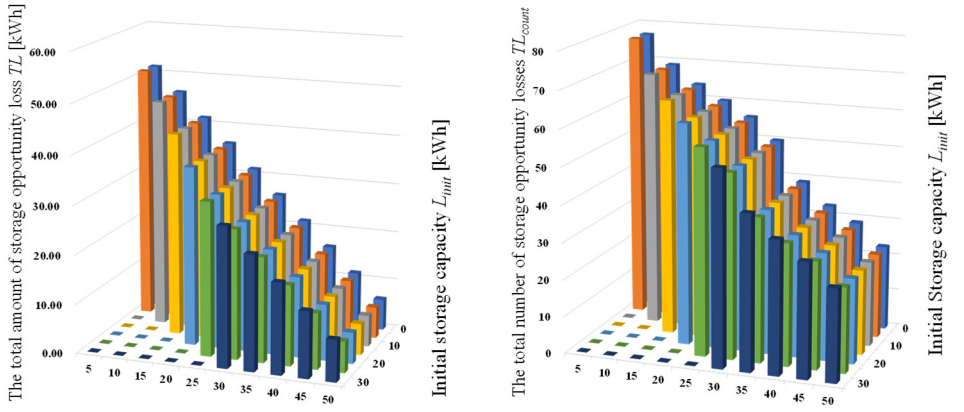


Figure 13. Changes in the power purchase amount at $L_{max} = 10$ [kWh] and $L_{init} = 0\,, 5\,, 10$ [kWh].



(a) Total amount of storage opportunity loss TL (b) Total number of storage opportunity losses TL_{count}

Figure 14. Sensitivity analysis for total amount of (**a**) storage opportunity TL and (**b**) total number of storage opportunity losses TL_{count}.

Figure 14b shows the results of the sensitivity analysis for the total number of storage opportunity losses TL_{count}. Similar to the total number of power purchases TP_{count}, the changes in the total storage opportunity loss amount TL generally corresponded with those in the total number of storage opportunity losses TL_{count}. However, decreases in TL were inconsistent for locations where L_{init} or L_{max} changes of 5 [kWh] were observed in the inventory amount. The reason for this is that the storage amount reached L_{max} on 22 August, when the private power generation greatly exceeded power consumption. Thus, a large amount of power was stored, and the timing at which the storage opportunity loss occurred varied according to each L_{max}.

Figure 15 shows the changes in power purchase amount when $L_{init} = 0$ [kWh] and the maximum storage amount $L_{max} = 0,\ 5,$ or 10 [kWh]. The changes in TL_{count} are also added.

4.2. Feedback

We received feedback from the staff of Ecolomy Co., Ltd. regarding the analysis results relating to the application of the on-demand DSMM to solar power generation. The applicability of this study is investigated based on this feedback:

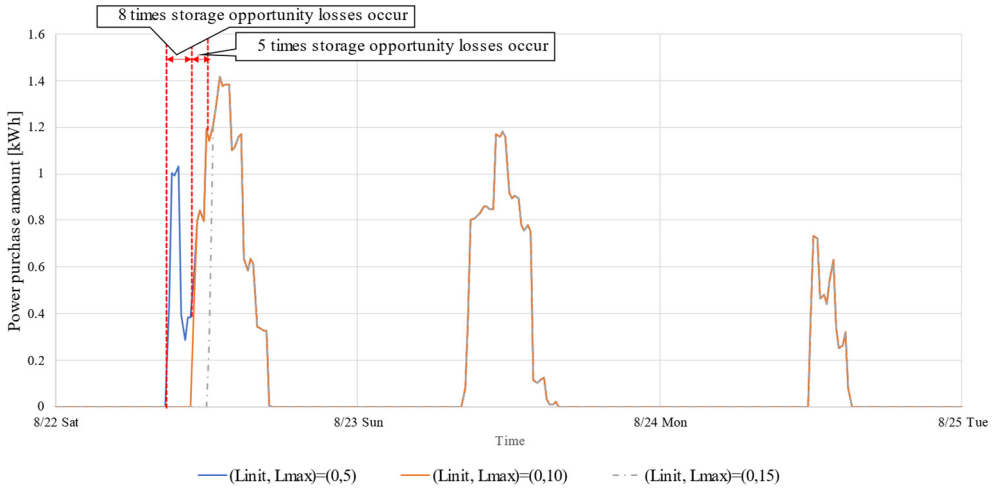


Figure 15. Changes in the power purchase amount when the initial inventory amount $L_{init} = 0$ [kWh] and the maximum storage capacity $L_{max} = 0,\ 5,\ 10$ [kWh].

- We received a positive opinion regarding the sensitivity analysis results of the total power purchase amount *TP*. They stated that "it is great that even a 20 [kWh] storage battery can achieve the same effect as a 40 [kWh] storage battery depending on how it is used." This opinion indicates that the modeling of demand-to-supply management of solar power generation using the on-demand demand-to-supply management method was useful;
- We also received a comment stating that "there is a sufficient amount of solar energy falling on the earth. However, we have heard that the technology for fully utilizing this is insufficient, and a storage battery with infinite capacity would be desirable if feasible." The importance of demand-to-supply management that seeks a realistic storage capacity or initial storage amount was also recognized once again.

4.3. Discussion

This section summarizes the findings of the results in Sections 3 and 4 along with RQs in Section 1.

RQ1. What are the managerial issues including capital investment in a transition to solar power generation in the targeted renewable energy company?

As per the answers to RQ1 based on the company interviews in step 1, the main managerial issue was the high initial introduction costs of a solar energy system with a larger capacity storage battery. The second issue was a too large variance to make proper predictions of electric power demand on a household basis. Therefore, it turned out that a methodology for dealing with the uncertainty of solar power generation under limited battery capacity, such as the DSMM and OCCM, is required.

RQ2. How was the demand-to-supply balance between the amount of electricity consumption and the amount of on-site solar power generation at the target facility?

As per the answer to RQ2 based on the results in steps 2 and 3, the difference in the cumulative amounts of power demand and private power supply during the week analyzed at the facility in Tokyo was only 8%. This fact means that appropriate demand-to-supply management could be employed to cover the private consumption with private power generation from solar power sources. However, 47% of the cumulative power consumption was discarded due to a dynamic gap between power demand and supply. As a result, it indicated that private power generation was not fully utilized, therefore, battery storage is helpful to satisfy the dynamic gap.

RQ3. How to operate a battery more effectively by applying a demand-to-supply management developed in production and logistics? Additionally, how was the moving base storage capacity for on-demand DSMM?

They are answered from the results in step 4. The morning from 06:00 to 12:00 and the early evening around 16:00 were the hours when the power consumption amount of the facility began to increase. Therefore, in order to operate the battery more effectively, the private power generation would be charged to the battery storage in the hours from 13:00 to 15:00, before the early evening.

Additionally, it is found that the moving base storage capacity N_t became 0 for saving the power purchase when an increase in storage amount was detected.

RQ4. What was the effect of the day of the week, time of day, and weather on the demand-to-supply management in solar-power generation at the target facility?

Regarding the day of the week: on weekdays, the power consumption amount was larger than the private power generation based on the results in Section 3.3. The average power purchase amount was 30 [kWh] and the average of private power generation was 17 [kWh] on weekdays. However, on Saturday and Sunday, the power consumption amount was lower than the private power generation. For the time of day, power consumption exceeded that of private power generation during the morning hours of 6:00–12:00 and the afternoon hours around 16:00 for all days except Sunday and holidays, when the facility was closed. With respect to the weather, the power generation efficiency actually depended on the weather in the week. The amount of solar power supply per day on cloudy and sunny days was twice and 4 times higher than that on rainy days, respectively.

RQ5. How effective are the capacity of the battery and the initial storage in the battery? Moreover, what is the energy storage opportunity loss at that time?

Since the introduction costs of storage batteries are very high, a large initial inventory with a small battery was effective such as L_{max} = 20 [kWh] and L_{init} = 20 [kWh] from the results in Section 4. At that time, the total storage opportunity loss amount TL become 46.36 [kWh].

The above discussions demonstrate that the proposed on-demand DSMM and OCCM could be useful and applied for demand-to-supply management of solar power generation and self-consumption.

5. Conclusions

This study applied the demand-to-supply management method (DSMM) and its development method of the on-demand DSMM to the solar energy at a facility.

The effective maximum and initial storage amount could be obtained simultaneously through the on-demand DSMM. Therefore, it demonstrates that the on-demand DSMM could be applied to demand-to-supply management of renewable power generation. Moreover, it was also shown that power consumption at times when renewable power was unable to generate could be covered by introducing a storage battery, and the battery capacity and storage required for smooth operation of the renewable system could be calculated using the on-demand DSMM. The main conclusions are as follows.

- The proposed method enables us to pre-process the private power generation data and align them to the same timescale as recorded for power consumption;
- The difference in the cumulative power consumption and the private power generation amounts during the course of the week analyzed was minimal. Results show that appropriate demand-to-supply management could be employed to cover private consumption with private power generation from PV sources;
- The cumulative amount of power purchased during this one week, however, corresponded to approximately half of the cumulative power consumption. It was also shown that the total number of power purchases comprised ~70%, indicating that private power generation was not fully utilized;

- Power consumption exceeded that of private power generation during the morning hours of 6:00–12:00, and the afternoon hours around 16:00 for all days except Sunday, when the facility was closed. It was also shown from shifts in the updating of $\overline{\beta}_t$ by Matsui logic that these were crucial hours for demand-to-supply management;
- It was shown that in the moving base storage amount obtained from the cumulative probability distribution of the remaining storage amount on a cloudy day, it was difficult to manage days where the daylight hours and total solar radiation were favorable or holidays where power consumption was minimal;
- A sensitivity analysis of the total power purchase amount showed that an effective combination of the initial and the maximum storage amount could be obtained simultaneously through the on-demand DSMM;
- The amount of changes in the total number of power purchases was inconsistent;
- It was not preferable to have a certain amount of initial inventory when setting the supply–demand management start day as Thursday because the storage opportunity loss would arrive earlier due to a full charge;
- With regard to the storage opportunity loss amount, it was found that the total number of storage opportunity losses did not necessarily correspond to times when there was a change of 5 [kWh];

These results indicate that the on-demand DSMM could be applied to, and useful for, demand-to-supply management of solar power generation. It was also shown that power consumption at times when solar was unable to generate could be covered by a storage battery, and the battery capacity and the storage required for optimal operation of the solar system could be calculated using the on-demand DSMM.

Future studies should include the extension of the target period of the data, management of the considered storage amount for seasonal fluctuations to further increase accuracy, proposal of a demand-to-supply management method that can accommodate for a wider range of demand situations by extending target facilities, and use of a moving average that can smooth data against power consumption of highly variable data. Additionally, future expectations include the following: the proposal of a model that can obtain economical storage battery capacity; application to a network of local production for local consumption within a community, called a microgrid; and building a model that enables stable power generation in combination with other renewable energy sources.

Author Contributions: S.Y. and T.Y. conceptualized the goals and the aims of this study. S.Y., M.M. and T.Y. designed the methodology. S.Y. wrote the original draft assisted by H.I., H.I. and T.Y. shaped this manuscript based on the original draft. M.T. and M.M. provided their related studies. T.Y. acquired funds. S.Y. applied formulations assisted by M.M., S.Y. programmed and validated the formulation, and visualized the results with H.I. and T.Y., S.Y. conducted the numerical experiment, and H.I., T.Y. and M.M. reviewed it. T.Y. managed this project and supervised the overall content. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The notations used in this study.

Variables	This Study
I_t:	Sum of private power generation and purchased electrical power in period t [KWh]
I'_t:	Sum of the next private power generation and the next power purchase amount in period t [kWh]
O_t:	Power consumption amount in period t [kWh]
L_t:	Remaining storage capacity in period t [kWh]
N_t:	Moving base storage capacity in period t [kWh]
X_t:	Forecasted power consumption amount in period t [kWh]
λ_t:	Demand rate at period t
$\overline{\beta}_t$:	Input amount determination parameter in period t
S_t:	Private power generation in period t [kWh]
P_t:	Power purchase amount in period t [kWh]
Y_t:	Forecasted private power generation in period t [kWh]
Coefficient	
α:	Coefficient of real power consumption
β_1:	Cost coefficient for maintaining electricity storage [yen/kWh]
β_2:	Cost coefficient for understocked storage [yen/kWh]
β_3:	Cost coefficient for overstocked electricity is storage [yen/kWh]
Evaluation Value	
L_{init}:	Initial storage capacity [kWh]
L_{max}:	Maximum storage capacity [kWh]
L_{loss_t}:	Storage opportunity loss amount in period t [kWh]
TP:	Total amount of power purchase [kWh]
TP_{count}:	Total number of power purchases [number]
TL_{count}:	Total number of storage opportunity loss [number]

Table A2. Weather during surveyed period.

Date	Day and Night	Weather
20 August	Day	Rainy, then sometimes cloudy
	Night	Cloudy, with brief rain
21 August	Day	Cloudy, then rain for a while
	Night	Cloudy
22 August	Day	Cloudy, then sunny
	Night	Cloudy, sometimes sunny
23 August	Day	Cloudy, with brief sun
	Night	Cloudy, with brief sun
24 August	Day	Cloudy
	Night	Cloudy
25 August	Day	Cloudy, then rain for a while
	Night	Rainy, with brief cloud
26 August	Day	Rainy
	Night	Cloudy, sometimes rainy, then sunny for a while
27 August	Day	Cloudy
	Night	Cloudy, then rainy for a while

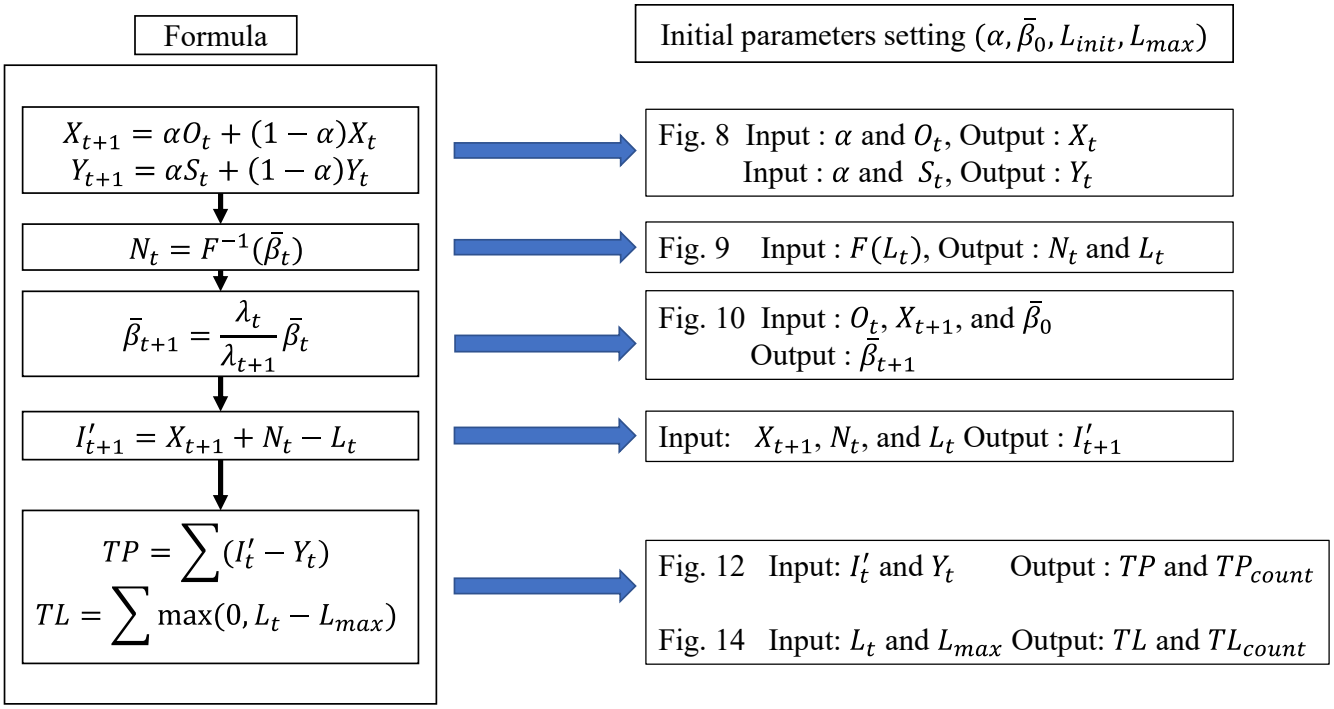


Figure A1. Input data including measurements and output data with the resulted main figures in Section 3.

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