Intermittent renewable energy, such as wind power and solar photovoltaic (PV), attracts great attention for addressing climate change and energy security concerns. This paper investigates the possible integration of massive wind power source into power generation mix using high time-resolution optimal power generation mix model which authors formulated as large-scale linear programming model including 2.5 million constraints and 1 million endogenous variables. The feature of the model allows us to explicitly consider actual wind and PV output variability in its time resolution of 10 minutes on each 365 day. Wind and PV output are estimated employing meteorological database. Simulation results reveal that, as wind installed capacity expands in the grid, the penetration level of wind power shows saturation trend and the suppressed wind output represents considerable increase when wind installed capacity reaches more than the same scale of the peak power demand.

Keywords
Batteries, Power generation dispatch, Power generation planning, Power system economics, Power system simulation, Solar power generation, Wind power generation

1. Introduction
In order to address the issue of climate change and energy security concerns, great attention has been introducing renewable energy, such as PV and wind power, and numerous countries like Japan [1], EU [2] and California [3] have mandated electric utilities to enhance the proportion of renewable energy in their power grid. Wind and PV power, however, are susceptible to weather conditions and tend to be volatile. If the introduction of wind and PV expands in power grid, important challenge is to effectively control their variability for integrating them with existing power grid and constructing optimal power generation mix in an efficient and reliable manner.

So far, elaborate analysis on optimal power plant operation under the variability of renewable focusing particularly on wind power has been conducted using cost minimization approach [4]-[8]. However, many assessments have not yet been conducted identifying the optimal power generation mix including rechargeable battery technology and suppression control measure under very high penetration level of variable renewable sources like wind and PV in high time resolution such as five or ten minutes considering their short-period variation in longer time period like 365 days.

In this paper, authors develop high-time resolution optimal power generation mix (OPGM) model, as large-scale linear programming model, which is capable of analyzing the optimal deployment of variable renewables, rechargeable battery technology and suppression control measure in electric power system in the time resolution of 10 minutes during 365 days. The feature of the model is that considered time resolution is 10 minutes in each 365 day, which allows us to analyze the impact of various short-period variations of wind and PV power on optimal power generation mix, and that various technologies for controlling the intermittency is comprehensively considered such as charge-discharge control of stationary sodium-sulfur battery technology [9], pumped-storage hydro, load following control by thermal power plant and the output suppression control of PV and wind. Up to now, the authors developed OPGM model and analyze the impact of PV system on electric power system [10][11]. This paper more focuses on analyzing the impact of very enormous wind power integration on power grid and identifies the maximum potential of wind energy penetration in Japan.

This paper is organized as follows: Section 2 reviews the potential of Japanese wind resource, and Section 3 provides the mathematical formulation of high time-resolution optimal power generation mix model. Section 4 explains simulation results under the level of various installed capacity of wind power and analyse the sensitivity impact of battery cost on power generation mix. In Section 5, conclusions are explained and future direction of research is suggested.
2. Wind Potential in Japan

The Japanese government aims to enhance up to 35% of Japan’s energy requirements to be covered by renewable sources by 2030, increasing up from about current 10%. Hydro power is the largest renewable source in Japan, with solar, wind and geothermal energy edging up to just about 1% of total power generation. For achieving that ambitious renewable integration target, Japan introduced a feed-in tariff (FIT) system to promote renewable energy. The Japanese FIT system assigned 10 electric power utilities to purchase electricity generated by PV and wind, paying about 40 cents per kWh and 23 cents per kWh, respectively. PV payments are set for 20 years, wind for 15.

Table 1. Wind power resource potential in Japan [12]

<table>
<thead>
<tr>
<th>Region</th>
<th>Onshore Wind</th>
<th>Offshore Wind</th>
<th>Total Electric Power Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hokkaido</td>
<td>140</td>
<td>403</td>
<td>7</td>
</tr>
<tr>
<td>Tohoku</td>
<td>73</td>
<td>225</td>
<td>17</td>
</tr>
<tr>
<td>Tokyo</td>
<td>4</td>
<td>79</td>
<td>64</td>
</tr>
<tr>
<td>Hokuriku</td>
<td>5</td>
<td>62</td>
<td>8</td>
</tr>
<tr>
<td>Chubu</td>
<td>8</td>
<td>39</td>
<td>33</td>
</tr>
<tr>
<td>Kansai</td>
<td>13</td>
<td>25</td>
<td>34</td>
</tr>
<tr>
<td>Chugoku</td>
<td>9</td>
<td>152</td>
<td>12</td>
</tr>
<tr>
<td>Shikoku</td>
<td>5</td>
<td>42</td>
<td>7</td>
</tr>
<tr>
<td>Kyushu</td>
<td>21</td>
<td>455</td>
<td>29</td>
</tr>
<tr>
<td>Okinawa</td>
<td>6</td>
<td>91</td>
<td>0.2</td>
</tr>
<tr>
<td>Total Japan</td>
<td>283</td>
<td>1,573</td>
<td>202</td>
</tr>
</tbody>
</table>

Reflecting on energy security issues and climate change concerns, great expectations have been placed on wind power generation in Japan as an indispensable technology to address those issues. Ministry of the environment in Japan officially estimated the potential of onshore and offshore wind energy potential in Japan [12]. This study has occasionally served as a basis for wind technological development in Japan. As shown in Table 1, it is assumed that maximum potential of installable wind power capacity in Japan amounts to about 280 GW in onshore and around 1600 GW in offshore which is together equal to more than 9 times of Japan’s grid scale or peak electricity demand (202 GW), and target wind power capacity by 2050 is formulated as 25 GW on onshore, 7.5 GW on deep-water offshore and 17.5 GW on floating offshore, backed by accelerated technical development. Thus in Japan, immense potential of wind power generation, 9 times of the peak demand or the grid scale, is expected to be exploited for the future for enhancing energy self-sufficiency and mitigating CO₂ emissions through the decreased reliance on fossil fuel. In this sense, it is important to estimate the possible large-scale integration of wind energy in Japanese power generation mix explicitly considering its short-term variation.

3. High-time Resolution Optimal Power Generation Mix Model

The authors develop high time-resolution optimal power generation mix model in the time resolution of 10 minutes on 365 days under various technical constraints employing linear programming technique[10][11]. The minimization of the single-period objective function, comprised of annual facility and fuel cost, allows us to identify the best mix of power generation and capacity of power plants for one year time horizon. The number of the constraints is about 2.5 million and that of endogenous variable is approximately 1 million. Exogenous variables such as cost and technical assumption are shown in Table 2. Regional scope in this paper is the whole region of Japan, although the model developed here is easily applicable to other region or country with just the change of exogenous variables. Problem formulation is described as follows:

Endogenous variables

\[ TC \]: total annual cost ($/year)
\[ X_{i,d,t} \]: output of \( i \)-th type of power plants in day \( d \) at time \( t \) (GW)
\[ K_i \]: capacity of \( i \)-th power plant (GW)
\[ C_{ha,j,d,t} \]: input of \( j \)-th electricity storage facility in day \( d \) at time \( t \) (GW)
\[ Dis_{j,d,t} \]: output of \( j \)-th electricity storage facility in day \( d \) at time \( t \) (GW)
\[ SS_{j,d,t} \]: stored energy of \( j \)-th storage facility in day \( d \) at time \( t \) (GWh)
\[ KS_1 \]: kW capacity of \( j \)-th electricity storage facility
\[ KS_2 \]: kWh capacity of \( j \)-th electricity storage facility
### Table 2. Exogenous variables [10]

<table>
<thead>
<tr>
<th>Type</th>
<th>Nuclear</th>
<th>Coal</th>
<th>LNG/GCC</th>
<th>LNG/GST</th>
<th>Oil</th>
<th>Biomass</th>
<th>Hydro</th>
<th>Geothermal</th>
<th>PV</th>
<th>Wind</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit Construction cost [$/kW]</td>
<td>1,500</td>
<td>2,800</td>
<td>1,200</td>
<td>1,200</td>
<td>1,900</td>
<td>3,500</td>
<td>8,500</td>
<td>5,100</td>
<td>4,000</td>
<td>2,400</td>
</tr>
<tr>
<td>Life Time [year]</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>60</td>
<td>60</td>
<td>17</td>
<td>17</td>
<td>17</td>
</tr>
<tr>
<td>Annual O&amp;M Cost Rate</td>
<td>0.04</td>
<td>0.048</td>
<td>0.036</td>
<td>0.036</td>
<td>0.039</td>
<td>0.048</td>
<td>0.017</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Maximum Capacity [GW]</td>
<td>34 GW</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>23 GW</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minimum Capacity [GW]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Maximum Increase Rate of Output [1/hour]</td>
<td>0.58</td>
<td>0.82</td>
<td>0.82</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.31</td>
<td>0.31</td>
<td>0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>Maximum Decrease Rate of Output [1/hour]</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.58</td>
<td>0.58</td>
<td>0.58</td>
<td>0.58</td>
</tr>
<tr>
<td>Conversion Efficiency</td>
<td>1</td>
<td>0.418</td>
<td>0.57</td>
<td>0.396</td>
<td>0.94</td>
<td>0.2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Own Consumption Rate</td>
<td>0.04</td>
<td>0.061</td>
<td>0.02</td>
<td>0.04</td>
<td>0.045</td>
<td>0.13</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Fuel Cost [cent/specific unit]</td>
<td>1.67</td>
<td>8.367</td>
<td>51.985</td>
<td>51.985</td>
<td>70.197</td>
<td>12.25</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Heat Content [kcal/specific unit]</td>
<td>860</td>
<td>6139</td>
<td>13043</td>
<td>13043</td>
<td>9126</td>
<td>3585</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Carbon Content [kg/specific unit]</td>
<td>0</td>
<td>0.61752</td>
<td>0.7462</td>
<td>0.7462</td>
<td>0.78792</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Seasonal Peak Availability</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.8</td>
<td>0.783</td>
<td>0.85</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Annual Average Availability</td>
<td>0.85</td>
<td>0.783</td>
<td>0.833</td>
<td>0.8</td>
<td>0.783</td>
<td>0.85</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Share of Daily Start and Stop</td>
<td>0</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Minimum Output Level</td>
<td>0.3</td>
<td>0.3</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0.3</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Specific Unit</td>
<td>kWh</td>
<td>kg</td>
<td>kg</td>
<td>kg</td>
<td>kg</td>
<td>kg</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

where. $\{i \in \{1: \text{Nuclear}, 2: \text{Coal fired}, 3: \text{Natural gas GCC}, 4: \text{Natural gas fired}, 5: \text{Oil fired}, 6: \text{Biomass}, 7: \text{Hydro}, 8: \text{Geothermal}, 9: \text{PV}, 10: \text{Wind}\}$

$j \in \{1: \text{Pumped}, 2: \text{Battery (stationary sodium-sulfur battery)} \}$

$d \in \{1, 2, \ldots, D\}$ $D$ : number of the day per year ($D=365$ or $366$)

$t \in \{1, 2, \ldots, T\}$ $T$ : number of the time steps per day ($T=24*6=144$)

### A. Objective Function

Objective function is composed of annual fixed cost and fuel cost for one year time horizon. Annual fixed cost is calculated as multiplication of capital recovery factor, unit fixed cost ($/kW) and capacity (kW).

$$\min \quad TC = \sum_{j=1}^{10} (g_j \times pf_j \times K_j + \sum_{d=1}^{D} \sum_{t=1}^{T} pv(t) \times X_{i,d,t}) + \sum_{j=1}^{2} CS_j$$  \hspace{1cm} (1)$$

Where: $g_j$ : annual fixed charge rate of $i$-th type of power plant (capital recovery factor), $pf_j$ : unit fixed cost of $i$-th type of power plants($/kW)$, $pv(t)$ : unit variable cost of $i$-th type of power plants($/kWh)$, $CS_j$ : annual cost of $j$-th type of storage facility

$$CS_j = (gs1_j \cdot pf1_j \cdot KS1_j) + (gs2_j \cdot pf2_j \cdot KS2_j) + (pf3_j \cdot \frac{TChaj}{cycle_j})$$  \hspace{1cm} (2)$$

Where: $gs1_j$ : annual fixed charge rate for power component of $j$-th type of storage facility, $pf1_j$ : unit fixed cost for power component of $j$-th type of storage facility($/kW)$, $gs2_j$ : annual fixed charge rate for energy component of $j$-th type of storage facility, $pf2_j$ : unit fixed cost for energy component of $j$-th type of storage facility($/kWh)$, $pf3_j$ : unit fixed cost for consumable material, such as electrode, electrolyte and separator of battery technology, $cycle_j$ : maximum recharge times of $j$-th type of storage facility, $TChaj$ : annual total charged electricity of $j$-th type of storage facility($/kWh/year)$

Cost for battery system depends on the power (kW) and energy (kWh) capacity of the system [13]. According to this concept, the total cost for battery system, as described by equation (2), is decomposed into capital cost proportional to kW capacity including the power conditioning system, capital cost proportional to kWh capacity including battery capital cost and the cost of consumable parts incorporating electrode, electrolyte and separator [10]. The cost of consumable part depends on the number of charge and discharge cycle. As power storage system, this paper considers stationary rechargeable sodium-sulfur (NaS) battery and pumped hydro which are suitable at large-scale power generation facilities. And those cost information is derived from the Ministry of Economy, Trading and Industry Japan [14][15], while other published reports provide relevant cost information [16][17] as well.

This report incorporates NaS (sodium-sulfur) battery system as stationary rechargeable battery technology. The round-trip ac-to-ac efficiency of sodium-sulfur battery system is approximately 80%. The estimated lifetime of a sodium-sulfur battery is
approximately 15 years after 4500 cycles at 90% depth of discharge. Table 2 compares the specification of typical rechargeable battery technology. The energy density of NaS battery reaches 3 times as high as lead battery. Advantage of NaS battery consists in abundant component resource (Na, S) availability, high energy density (3 times as lead battery), high charge and discharge efficiency, long lifetime, no self-discharge and simple maintenance. Disadvantage of the NaS is that heating system to maintain 300 degrees is required, and component materials such as Na are flammable causing security issues.

Table 3. Performance of stationary rechargeable battery technology

<table>
<thead>
<tr>
<th></th>
<th>Lead</th>
<th>NaS</th>
<th>Ni-MH</th>
<th>LiB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy density (Wh/kg)</td>
<td>35</td>
<td>110</td>
<td>60</td>
<td>120</td>
</tr>
<tr>
<td>Energy Efficiency (%)</td>
<td>87</td>
<td>90</td>
<td>90</td>
<td>95</td>
</tr>
<tr>
<td>Lifetime (cycle)</td>
<td>4,500</td>
<td>4,500</td>
<td>2,000</td>
<td>3,500</td>
</tr>
<tr>
<td>Cost ($/kW)</td>
<td>1,500</td>
<td>2,400</td>
<td>1,000</td>
<td>2,000</td>
</tr>
<tr>
<td>Cost ($/kWh)</td>
<td>500</td>
<td>250</td>
<td>1,000</td>
<td>2,000</td>
</tr>
</tbody>
</table>

(Source) METI “Current Situation on Battery Technology” (in Japanese), Feb. 2012[18]

However, notable disadvantage of NaS battery is that the battery needs to be kept at about 300 degrees to maintain the liquid condition of sodium (negative electrode) and to facilitate its charge and discharge process. During its charging and discharging process, the battery is spontaneously maintained at 300 degrees due to self-heating derived from the process. Outside the process, it is necessary to keep the temperature by electric heating system. Electricity consumption in the heating system is typically around 50 kW at 1,000 kW NaS battery. Considering those things, in the case of NaS battery with the scale of 1,000kW as kW-capacity and 8,000 kWh as energy capacity, electricity consumption in the heating on 1 day is equal to 50 kW × 24 hour = 1,200 kWh, accounting for about 15% (=1,200/8,000) of electricity stored in the battery. This energy loss should be fully considered in evaluating the economic performance of the system with NaS battery and the computer simulation on this report explicitly incorporates this inefficiency.

B. Constraints

<Power demand and supply balances>

\[ \sum_{i=1}^{10} X_{i,d,t} + \sum_{j=1}^{2} (\text{Dis}_{j,d,t} - \text{Cha}_{j,d,t}) = \text{load}_{d,t} \]  \[ (4) \]

Where: \(\text{load}_{d,t}\) : electric load in day \(d\) at time \(t\)

<Available capacity constraint>

Equation (6) defines that battery power is charged and discharged under its available kW capacity. In PV and wind, the availability factors \(u_{i,d,t}\) in equation (5) are given in the time resolution of 10 minutes during 365 days as later shown in Fig.3 and Fig.6.

\[ X_{i,d,t} \leq u_{i,d,t} \times K_i \]  \[ (5) \]

\[ \text{Cha}_{j,d,t} + \text{Dis}_{j,d,t} \leq u_{S1,j,t} \times K_{S1,j} \]  \[ (6) \]

\[ SS_{j,d,t} \leq u_{S2,j,t} \times K_{S2,j} \]  \[ (7) \]

Where: \(u_{i,d,t}\) : availability factor of \(i\)-th type of power plant, \(u_{S1,j,t}\) : kW availability factor of \(j\)-th type of storage facility, \(u_{S2,j,t}\) : kWh availability factor of \(j\)-th type of storage facility

<Upper and lower installable capacity constraint>

\[ K_i \geq K_{i,0}, K_i \leq K_{i,upper} \]  \[ (8) \]

\[ KS_{S1,j} \geq KS_{S1,j}, KS_{S1,j} \leq KS_{S1,upper,j} \]  \[ (9) \]

\[ KS_{S2,j} \geq KS_{S2,j}, KS_{S2,j} \leq KS_{S2,upper,j} \]  \[ (10) \]

Where: \(K_{i,0}\), \(KS_{S1,j}\), \(KS_{S2,j}\) : existing capacity, \(K_{i,upper}\), \(KS_{S1,upper,j}\), \(KS_{S2,upper,j}\) : capacity upper limit
<Capacity reserve constraint for supply reliability>

\[
\sum_{i=1}^{5} u_{i,d} \times K_i + \sum_{j=1}^{2} w_{1,j,d} \times KS1_j \geq (1 + \delta) \times \text{load}_{d,d} \quad (11)
\]

Where: \( d \) : reserve margin (=5–8%).

<Load following capability constraint>

Each type of power plant has its own load following capability. The parameter \( \lambda_i \) is introduced to relax the load following constraints [10]. In the case where \( \lambda_i \) is assumed to be equal to 0, power generation \( X_{i,d,t} \) cannot be zero, or must be kept at zero over the whole time of the year once \( X_{i,d,t} \) becomes zero.

\[
X_{i,d,t} \leq X_{i,d,t} + \text{increase}_i \times \{(1 - \lambda_i) X_{i,d,t} + \lambda_i \times u_{i,d} \times K_i\} \quad (12)
\]

\[
X_{i,d,t} \geq X_{i,d,t} - \text{decrease}_i \times \{(1 - \lambda_i) X_{i,d,t} + \lambda_i \times u_{i,d} \times K_i\} \quad (13)
\]

Where: \( \text{increase}_i \) : maximum output increase rate per unit time of \( i \)-th type power plant, \( \text{decrease}_i \) : maximum output decrease rate per unit time of \( i \)-th type power plant, \( \lambda_i \) : capacity weight in the present output level (=0.5 for default setting in this study).

<Minimum output constraint on thermal power plant>

Equation (14) explains that thermal power plant operates over minimum output threshold excluding the thermal plant dedicated for DSS (Daily Start and Stop) operation (\( \text{dss} \))[10]. For sharp demand peak within a day, thermal plant with DSS mode generates electricity under cyclic operation consisting of rapid heat-up and cool-down for varying demand. Minimum output level of thermal plant (\( \text{mol} \)) in equation (14) is calculated on the basis of its maximum output level (\( D_{\text{Max}} \)) identified through equation (15) and (16).

\[
X_{i,d,t} \geq (D_{\text{Max},i,d} - \text{dss}_i \times u_{i,d} \times K_i) \times \text{mol}_i \quad (14)
\]

\[
D_{\text{Max},i,d} \geq X_{i,d,t} \quad (15)
\]

\[
D_{\text{Max},i,d} \geq X_{i,d,t+1,t} \quad (16)
\]

Where: \( D_{\text{Max},i,d} \) : maximum output level of \( i \)-type power plant in day \( d \) and \( d+1 \), \( \text{dss}_i \) : share of daily start and stop operation (DSS) of \( i \)-type power plant, \( \text{mol}_i \) : minimum output level ratio of operation of \( i \)-th type power plant.

<Charge and discharge balances of rechargeable battery technology>

State equation (17) explains the balance of power charge and discharge for stored electricity in storage facility [10].

\[
SS_{j,d,t+1} = (1 - s_{d,j}) \times SS_{j,d,t} + (\sqrt{\text{eff}_{\text{storage},j} \times \text{Ch}_{j,d,t}} - \frac{1}{\sqrt{\text{eff}_{\text{storage},j}}}) \times \text{Dis}_{j,d,t} \times Tw \quad (17)
\]

<Available capacity constraint of battery technology>

\[
SS_{j,d,t} \leq m_{\text{storage},j} \times u_{j,d} \times KS1_j \quad (18)
\]

Where: \( s_{d,j} \) : Self discharge rate, \( \text{eff}_{\text{storage}} \) : Cycle efficiency of electricity storage, \( m_{\text{storage}} \) : Energy storage capacity per generation capacity, \( Tw \) : step width of the unit time (10 minutes).

<CO2 emissions constraint>

\[
\sum_{i=1}^{5} (\text{carbon}_i \times \sum_{d=1}^{D} \sum_{t=1}^{T} X_{i,d,t}) \times Tw \leq \text{co2}_{\text{upper}} \quad (19)
\]

Where: \( \text{carbon}_i \) : Carbon intensity of fuel of \( i \)-th type power plant, \( \text{co2}_{\text{upper}} \) : Emission limit.

Besides the above constraints, additional constraint is considered so that, for fuel diversification, annual total power generation of gas-fired power plant is equal to that of coal-fired power plant. The yearly profile of the average outputs of PV and wind at ten minutes interval, corresponding to \( u_{i,d,t} \) in equation (5), are estimated using the Japanese meteorological...
database [19], which provides observed data of insolation and wind speed etc. on every 10 minutes. If the data like one or five minutes are available, the model can be adjusted to that resolution. The optimal power generation mix model in this study adopts annual load curve information on a daily basis. The Japanese whole load curves for the model is estimated from the following available information: amounts of daily electricity demand of each regional electric power company since 1st of April 2005; Daily peak load of each regional company since 1st of April 2005; Representative daily load curves of seven daily patterns for some regions before 1995. In addition, annual electricity demand quantity is assumed to be 1,000 TWh according to current Japanese electricity demand level. Fig.1 shows the estimated daily load curve in the resolution of 10 minutes on 365 days a year.

![Electricity Demand](image)

**Fig. 1** Daily load curve of Japan in 365 days at 10 minutes’ interval.

3. Intermittent renewable power generation

3.1 Photovoltaic power generation output

AMeDAS (Automated Meteorological Data Acquisition System) [19] is a weather observation system that covers Japanese island. The system extends to about 1,300 places in its territory, and measures precipitation, wind direction, wind velocity, temperature, durations of sunshine, and depth of snow cover by automatic operation at ten-minute interval. The yearly time profile of the regional average outputs of PV power generation at ten minutes interval on 686 observations site in Japan were estimated by using the numerical solar irradiance model with AMeDAS observation data on sunshine duration, precipitation and ambient temperature. Fig.2 shows the calculation flow of PV output at each AMeDAS observation site. The regional average PV output of unit capacity were derived from simple arithmetic average of the estimated PV outputs of unit capacity at almost all of AMeDAS observation sites in Japan.

![Calculation flow of PV output](image)

**Fig. 2** Calculation flow of PV output for each site.

AMeDAS sites at which the sunshine duration data were not properly observed, are excluded in the regional averaging process. The total solar radiation on tilted plane was derived from the modification of that on horizontal plane with the azimuth angle (south) and tilted angle (16°:average roof slope of Japanese houses) of installed PV arrays. And, the PV output of unit capacity at
the site was estimated on the basis of the total solar radiation on tilted plane and system output coefficient that was slightly affected by temperature of PV cells. Finally, the Japan’s whole PV output is calculated from the weighted average of the derived regional PV output of unit capacity on regional prospect of newly-building detached house and uncultivated farmland area.

The estimated PV outputs of unit capacity in Japan during the year 2007 are shown in Fig.3, which indicates that PV output tends to be larger in summer and smaller in winter season. Annual average utilization rates of PV generation in each AMeDAS observation site is illustrated in Fig.4 [10].

![Fig. 3 PV output pattern of whole Japan in 365 days at 10 minutes’ interval (2007).](image)

**Fig. 3** PV output pattern of whole Japan in 365 days at 10 minutes’ interval (2007).

![Fig. 4 Annual average utilization rates of PV generation in Japan [10].](image)

**Fig. 4** Annual average utilization rates of PV generation in Japan [10].

### 3.2 Wind power generation output

Japan’s total outputs of wind power generation at ten minutes interval is estimated employing the AMeDAS metrological observation data as well. Fig.5 indicates the calculation flow of the wind output at each observation site. We first estimated the yearly time profile of the wind power output of unit capacity by the observation site, and then derived the time profile of regional average on the basis of geographical distribution of wind power generation capacities within the regions in the end of 2007. In Japan, the majority of onshore wind resources concentrate on Hokkaido and Tohoku regions (North part of Japan) as previously sown in Table 1, and therefore, the whole pattern of wind output in Japan is calculated using a weighted average of the derived regional wind power output in the amount of regional wind resources. Fig.6 illustrates wind generation pattern in the resolution of 10 minutes in 365 days a year.
4. Simulation Results

4.1 Power Generation Mix

As explained in chapter 2, Japan is currently aiming to expand installed wind capacity in electricity system to around 50 GW by 2050, and Japanese government estimates technically installable wind capacity in Japan as around 1800 GW, which is 9 times of the grid scale in Japan. These investigations suggest an enormous wind installable potential enough to cover a large portion of electricity demand in Japan.

Against this background, we conduct the sensitivity analysis on installed wind capacity covering from 5 GW to 800 GW at intervals of 50 GW to 100 GW, and calculate the optimal power generation mix in each given wind capacity using the OPGM model described in Section 3. Maximum end of the sensitivity analysis corresponds to approximately a half of deployable wind resource potential in Japan. The following calculated results basically refer to the scale of wind installed capacity normalized by peak demand or grid scale.

Fig. 7 shows the configuration of power generation mix in individual given installed wind power capacity. As installed wind power expands in Japan’s electricity system, based on Fig.7(a), it seems to mainly replace thermal power generation and encourage the suppression control of wind power generation. Charge and discharge cycle of rechargeable battery technology does not so much appear even in the massive penetration of wind power mainly due to its more expensive cost compared with other measures such as the suppression control and quick load following of thermal power plant. Focusing on wind power penetration level in on Fig.7(a), the wind power integration in power generation mix becomes incrementally saturated and the suppression control of wind power considerably increases as installed wind expands in the grid.
4.2 Optimal Power Generation Dispatch

Simulated monthly optimal operation of power generator in May and August are respectively shown in Fig.8 and Fig.9 on given installed wind power capacity at from 0.25 to 4.0 times of the peak demand. In our analysis, the optimal operation is identified so as to minimize the total system cost under various technical constraints. In accordance with this metric, it turns out that renewable variability is technically controlled by power charge and discharge cycle of energy storage technology such as pumped-hydro, load following operation by thermal power plant and the output suppression control of wind power, which implies that a variety kind of measures potentially function as a whole to control the short-period variation of renewables output.

As already shown in wind output profile in Japan on Fig.6, wind velocity shows seasonal imbalance such that wind power has higher intensity in spring and winter season and lower intensity particularly in summer season when alternative power generator is necessary to compensate these imbalances in the condition that wind power are massively integrated in the grid. On May when large-scale wind power output can be expected, intensive curtailment of wind power is observed under the condition that installed wind capacity reaches more than the same scale of the peak demand, based on from Fig.8(c) to Fig.8(f).
Fig.8 Simulated monthly power generation profile in May (May 1-May 31) at 10 minutes’ interval.
Fig. 9  Simulated monthly power generation profile in August (August 1-August 31) at 10 minutes’ interval.
In August when wind power supply tends to be relatively decreasing compared with other months, the elaborate suppression control of wind power output is implemented in the condition that installed wind capacity reaches more than double the scale of the peak demand as observed in from Fig.9(d) to Fig.9(f), and LNG gas combined cycle alternatively plays an important role to compensate the decreasing output of wind power in August.

### 4.3 Suppression Control (Curtailment) of Wind Power

Suppression rate is defined as the portion of curtailed wind power generation over total wind power generation in individual time unit (10 minutes). Fig.10 illustrates the suppression rate of wind power generation on each 365 day at 10 minutes’ time resolution, in which vertical axis shows time of the day in 10 minutes, and horizontal axis, 365 days.

**Fig. 10** Suppression rate of wind power generation on each 365 day at 10 minutes’ time resolution.
The Fig.10 indicates that the install of wind power at more than the half of the peak demand causes the significant suppression control, and the suppression rate of wind in Japan tends to become higher in winter and spring seasons, because wind velocity remains higher as shown in Fig.6 while the level of electricity demand is modest at those seasons. By contrast in summer season, Fig.10 reveals the lower curtailment rate due to the decreasing wind output intensity as illustrated in Fig.6. In May, the wind suppression rate is observed to reach around 60% in the case of wind capacity at 1.0 times the peak load (almost the same scale of the grid), and to show approximately 80% in PV installation at 2.0 times the peak load.

Fig.11 shows wind power generation supplied into the grid and the suppressed amount of wind output on each given installed capacity of wind power. This figure conducts the sensitivity analysis on given installed wind capacity covering from 5 GW extensively to 1400 GW, near value of maximum wind potential in Japan. In the figure, horizontal axis shows given wind capacity normalized with the peak demand, while vertical axis is wind power generation normalized by total annual electricity demand. According to Fig.11, as wind installed capacity increases up to almost the half of the scale of peak demand, wind power generation is supplied into the grid almost without the suppression control. Under the wind install at more than half of the scale of peak demand, the ratio of suppressed wind power shows significant increase: on wind installed capacity at the same, double and triple of the peak demand, the ratio of suppressed output in total wind power generation shows 20%, 40% and 60% respectively. Thus, the scale of wind power integration into the grid becomes incrementally saturated and converged at certain level even as installed wind capacity massively expands in the grid due to the growing fraction of wind output suppression. Fig.11 also suggests that wind penetration level seemingly shows very sluggish growth even by expanding wind capacity at more than 2 times of the peak demand, although Japan has immense wind installable potential equivalent to 9 times of the peak demand as previously explained in chapter 2.

![Wind power generation into the grid and its suppressed output on each given installed capacity of wind power.](image)

### 4.4 Sensitivity Analysis on Battery Cost

Fig.11 in section 4.3 suggests that the suppression control is one of key options to control the output of variable renewables, and the magnitude of the suppression is considered to be related to the installed rechargeable battery capacity. This section deals with the sensitivity analysis of stationary sodium-sulfur (NaS) battery cost on the given installed wind capacity at 300 GW, corresponding to 1.5 times the scale of the grid. As described in Table 4, five cases are supposed about the battery cost: current cost values (Base), Japanese governmental R&D targets (-90%)[15] and intermediate between the current cost and the governmental targets (-25%, -50%, -75%). For energy storage application to stabilize power system, Japanese official roadmap [15] sets a target of reducing the cost by 90% until 2030 from the current technical level.

<table>
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<tr>
<th></th>
<th>Base</th>
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<th>-50%</th>
<th>-75%</th>
<th>-90%</th>
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<td>4,875</td>
<td>5,250</td>
<td>5,625</td>
<td>6,000</td>
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</tbody>
</table>
Fig.12  Power generation mix in respective cost scenario of rechargeable sodium-sulfur (NaS) battery.

Note: Sensitivity analysis of stationary sodium-sulfur (NaS) battery cost is conducted on the given installed wind capacity at 300 GW, corresponding to 1.5 times the scale of the grid.

Fig.12 depicts power generation mix in respective cost scenario of rechargeable NaS battery technology on the given installed wind capacity at 1.5 times the scale of the grid, and Fig.12(c) shows power generation focusing on wind, suppressed wind and charged power into battery. As the battery cost becomes lower, more battery capacity is observed to be installed, while the output suppression of wind power is decreased as shown in Fig.12(b) and Fig.12(c). In low battery cost case, wind power generation in to the grid increases from the base case cost due to the improved economic performance of the rechargeable battery. This sensitivity analysis of battery cost shows that lower battery cost increases the installed battery capacity and decreases the suppression control.
of wind power, which suggests that the reason of wind power suppression instead of storing surplus wind power is due to the higher cost of rechargeable battery technology.

Fig. 13 shows installed rechargeable NaS battery capacity of kW and kWh (energy) in respective cost scenario of the rechargeable battery. As the battery cost decreases, its kWh(energy)-capacity represents more rapid growth compared with its kW-capacity. In the battery cost 90% reduction case, the ratio of install battery kWh-capacity to kW-capacity amounts to around 30 hours, which suggests that NaS battery is introduced to charge the surplus wind power in a longer time interval, such as on a weekly basis. Fig.14, Fig.15 and Fig.16 illustrate SOC (State of Charge) of installed sodium-sulfur battery in respective battery cost scenario on May, August and a whole year in 10 minutes’ time resolution, which ensures that NaS battery is installed for storing surplus wind power chiefly in a weekly scale, not so much in a daily scale.

And Fig13(c) compares the capacity of installed wind power and rechargeable sodium-sulfur battery. With the suppression control allowed in the grid, the required capacity of NaS battery shows 20% to 30% of the installed wind capacity. The suppression control diminishes the installed capacity of NaS battery and enhances the economic performance of renewable energy system.

![Fig.13 Installed rechargeable battery capacity in respective cost scenario of sodium-sulfur (NaS) battery.](image)

Note: Sensitivity analysis of stationary sodium-sulfur (NaS) battery cost is conducted on the given installed wind capacity at 300GW, corresponding to 1.5 times the scale of the grid.

![Fig. 14 SOC (State of Charge) of rechargeable sodium-sulfur battery in respective battery cost scenario on May.](image)

Note: Sensitivity analysis of stationary sodium-sulfur (NaS) battery cost is conducted on the given installed wind capacity at 300GW, corresponding to 1.5 times the scale of the grid.
Fig. 15  **SOC (State of Charge) of rechargeable sodium-sulfur battery in respective battery cost scenario on August.**

Note: Sensitivity analysis of stationary sodium-sulfur (NaS) battery cost is conducted on the given installed wind capacity at 300 GW, corresponding to 1.5 times the scale of the grid.

Finally, Fig.17 illustrates the simulated suppression rate over a whole yearly wind power generation. In low battery cost scenario as shown in Fig.16 (b), the intensity of the suppression rate tends to become significantly lower compared with Fig.16(a) with the base case of battery cost, principally due to the increased installed capacity of rechargeable NaS battery as illustrated in Fig.12 and Fig.13. Based on these results, the reason to curtail wind output instead of storing the surplus wind power is chiefly attributable to the high cost of stationary battery technology. If battery cost is expensive and not so much installed, the suppression rate is higher, and vice versa.
5. Conclusions

The massive integration of variable renewable resources into power grid is considered as an important measure toward enhancing energy self-sufficiency and tackling global climate change. However, this integration is complicated by intermittency and uncertainty of variable renewable output. This paper develops high time-resolution optimal power generation mix model in the time resolution of 10 minutes on each 365 day which allows us to analyze the integration of massive variable renewables into electricity system. This model is expected to contribute to the successful economic integration of variable renewable in policy-making situation and may provide additional insight regarding massive deployment of variable renewables. It should be kept in mind, however, that our analysis assumes wind and PV output as given variable and does not include the technical preparation, such as excessive battery capacity and backup generator, for unexpected disrupt fluctuation of those renewables as well as the technical measure for power system voltage and frequency fluctuations.

In the above limited framework, technical implication are obtained that the scale of wind power integration into the grid becomes incrementally saturated and converged at certain level even as installed wind capacity massively expands in the grid due to the growing fraction of wind output suppression and other technical limitations. The calculated results implies as well that wind penetration level seemingly shows very sluggish growth even by expanding wind capacity at more than 2 times of the peak demand, although Japan has immense wind installable potential equivalent to 8 times of the peak demand. However, it should be noted that this result might be changed depending on the assumption of base load capacity such as nuclear. Secondly, simulated results about daily optimal dispatch indicates that the variability from high penetration level of wind power is comprehensively controlled by quick load following by thermal plant together with battery and the suppression of PV and wind, which suggests that it is important to optimize multiple measures dynamically for the control of variable resources. Thirdly, the sensitivity analysis on rechargeable sodium-sulfur battery cost shows that lower battery cost increases the installed battery capacity and decreases the suppression rate of wind power, which suggests that the reason of wind power suppression instead of storing surplus wind power is due to the high cost of sodium-sulfur battery.
Future work is to investigate the impact of intermittent renewables on electric power system by considering transmission line as well as refining the modeling of load following and minimum output constraint in thermal power plants. Upgrading the single period model to multi-period model including economic retirement, replacement or retrofit of existing power generation with new one is important future consideration as well.

References


