Ramp Rates Control of Wind Power Output Using a Storage System and Gaussian Processes

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Abstract

This paper suggests the operation polices of storage devices to limiting ramp rates of wind power output. Operation polices are based on the optimization framework of linear programming under the assumption that there is a penalty cost for deviating outside ramp rate limits. Policies decide optimal storage operations to minimize the total penalty costs incurred when violating ramp rate limits. For the given generated wind power, the optimization framework decides the storage operation by considering the future wind power. Wind power outputs for six hours are forecasted by Gaussian Processes in order to reflect the trend of wind power in the optimization framework. Operation policies manages the state of charge (SOC) level optimally.

1 Introduction

Wind power is a promising renewable energy source, but it is variable. Wind turbines do not always generate power output at peak demand times, and their outputs fluctuate because of inherent wind speed variability, gusts, or diurnal trends. Although aggregating outputs from geographically distributed turbines smoothes the fluctuation, wind farms are still affected by large scale weather phenomena. Therefore, energy generated from base-load generators decreases, but energy generated from peak-load generators increases as the penetration level of the wind power increases. To be compatible with peak-load generators, ramp rates of wind power output should be limited to the ramping capabilities of peak-load generators. Limiting ramp rates can also reduce the amount of back-up power from peak-load generators.

Furthermore, severe ramp rates of the wind power could affect the stability where wind farms are interconnected, so system operators still consider it to be a burden to interconnect wind power with their conventional power system. Some electricity markets impose a ramp penalty for severe ramp-up/down events of the wind power output [1]. In this paper, it is assumed that the Electric Reliability Council of Texas (ERCOT) will charge the penalty to the stakeholders for violating ramp rate limits. The penalty is assumed to be linearly proportional to the number of [MW] above or below the ramp rate limits. Ramp-up rates can be limited by the wind power curtailment, and ramp-down rates can be supported by reserve services. However, wind power curtailment leads directly to a loss of profit for wind farm owners. Moreover, reserve services are managed by ERCOT, which leaves the wind farm owners no means to react on their own to ramp-down rates of wind power output.

1.1 Definitions of Ramp Events

A ramp event is defined as the power change event at every time interval. If the power change is positive, it is defined as a ramp-up event. If the power change is negative, it is defined as a ramp-down event. The rate of a ramp event is called a ramp rate, which is defined as the power difference from minute to minute, so its unit is [MW/minute]. The convention used here is that the ramp-up event has a positive ramp rate, but the ramp-down event has a negative ramp rate. There is a ramp-up rate limit and a ramp-down rate limit. Sum of net production and the ramp-up rate is called the ramp-up constraint. On the contrary, subtraction of ramp-down rate limit from the net production is called the ramp-down constraint. It is worth noting that ramp-up/down rate will be noted simply as ”ramp rate” unless the terms ”ramp-up rate” or ”ramp-down rate” need to be mentioned separately, throughout this paper.

1.2 Motivations

A storage system can reduce the ramp rate of the wind power by charging and discharging.When wind power violates the ramp-up limit, a storage reduces the curtailment by charging the unused power. When the wind power violates the ramp-down limit, a storage discharges to meet the required ramp-down rate limits. However, a decision process prohibiting deviation from ramp rate limits (RRL) requires the storage system to be very large and have a high power rating. If there is a penalty for deviating outside the RRLs, storage operation policies can be decided optimally by designing a linear program. Moreover, without forecasting the future wind power output, the decision at the current operation interval could be a shortsighted solution neglecting future ramp events and long-term trends. On the contrary, if a storage system can forecast the trend of short-term wind power output, the system can allocate the state of the charge (SOC) level wisely in preparation for severe ramp down or up events while minimizing the number of ramp rate violations.

The net production is defined as the sum of wind power output and output of storage operation.

1.3 Contributions and goals

Our ultimate goal is to decide the optimal power rating and storage size in order to minimize the sum of the investment cost of the storage and financial penalties.

1. Provide the optimization framework to control storage system.
2. Provide the point-forecasts of wind power output through the Gaussian Processes.
3. Utilize the forecasting information in the storage operation.
4. Limit ramp rates of wind power output

A linear program is designed to decide the optimal storage operation policies to limit ramp rates of the net production based on the forecasted path of the wind power. The path of wind power is forecasted by performing the point forecasting recursively. The next point is forecasted through a pattern matching algorithm which is Gaussian process.

1.4 Literature review

Studies provides that more variability is added to wind's variable nature by both seasonal and regional effect. [2] explains about the seasonal periodicity of wind speed on northwest region in Guyana coastlands. The seasonal periodicity is characterized by high mean wind speed during the northern winter and low means during the summer.

[3] shows information of wind generation impact on the U.S. power grid. [3] indicates that high percentage of wind will have an impact on power system operation and costs due to the variability of wind added to the already variable nature of the power system. [4] claims that the variability of wind generation can be balanced by using storage to keep the overall power output constant for five minutes.

A large wind ramping event in ERCOT, which took place on February 26, 2008 is case to show the effect of wind ramping on power grid. On February 26, 2008 ERCOT wind generation output at 2000 [MW] ramped down to 360 [MW] in 3 and a half hours [5]. The ramp down was 2 hours sooners and faster than the day ahead forecast. Furthermore, evening load ramped up quicker than was expected followed by unexpected loss of conventional generation. ERCOT resolved this ramp down event by calling on reserve capacity, including Loads acting as a Resource (LaaR).

Further details of February 26, 2008 event can be found in [5]. With more accurate forecast of generation and load, and support from storage operations are expected to give better prevention of this event.

1.5 Organization

The paper is organized as follows. The section 2 analyzes the characteristic of wind power variability and describes the forecasting method. The section 3 addresses the storage system model with loss, round-trip efficiency, power rating, and storage size. Section 4 introduces the variables in the linear program. In the section 5, the optimization framework is developed. In the section five, wind power output is simulated using a storage system. The final section is about the summary and future work.

2 Wind Power Forecasting

Wind power output is forecasted through the Gaussian processes. It is based on the assumption that the pattern of the current segment of wind power will matched with the patterns of historic wind power segments.

2.1 Gaussian Processes

Gaussian process is used as the forecasting technique. Gaussian process is an adequate tool for forecasting wind power because of the non-linear characteristic of wind.
To use Gaussian process we express observed target value (T_N) as the sum of function values ($f\left(x_N\right)$) and noise (ε_N) as shown in (1). The function values are assumed to be the known function values of the training cases which are in forms of Gaussian distribution. Because of the assumption any finite linear combination of observed target values has a joint Gaussian distribution.

$$T_1 = f\left(x_1\right) + \varepsilon_1,\ T_2 = f\left(x_2\right) + \varepsilon_2,\ ...,\ T_N = f\left(x_N\right) + \varepsilon_N \tag{1}$$

We express the function values as (2) where m is mean function and k is covariance function [6]. This (2) is used as a prior probability distribution over functions. At this point mean function and covariance function is assumed with a generalized equation such as shown in (3) with initial hyperparameters ($\alpha,\ \beta,\ \gamma,\ \sigma_y,\ \sigma_n$, and l) [7].

$$f \sim GP\left(m, k\right) \tag{2}$$

$$m\left(x\right)=\alpha x^{2}+\beta x+\gamma,\ \ and\ \ k\left(x,x'\right)=\sigma_{y}^{2}\exp\left(-\frac{\left(x-x'\right)^{2}}{2l^{2}}\right)+\sigma_{n}^{2}\delta_{ii'} \tag{3}$$

The right values of hyperparameters can be found by optimizing marginal likelihood (4) based on its partial derivatives shown in (5) and (6) [7].

$$L=\log p\left(y|x,\theta\right)=-\frac{1}{2}\log\left|\Sigma\right|-\frac{1}{2}\left(\mathbf{y}-\mu\right)^{T}\Sigma^{-1}\left(\mathbf{y}-\mu\right)-\frac{n}{2}\log\left(2\pi\right) \tag{4}$$

$$\frac{\partial L}{\partial\theta_{m}}=-\left(\mathbf{y}-\mu\right)^{T}\Sigma^{-1}\frac{\partial m}{\partial\theta_{m}} \tag{5}$$

$$\frac{\partial L}{\partial\theta_{k}}=\frac{1}{2}\mathrm{trace}\left(\Sigma^{-1}\frac{\partial\Sigma}{\partial\theta_{k}}\right)+\frac{1}{2}\left(\mathbf{y}-\mu\right)^{T}\frac{\partial\Sigma}{\partial\theta_{k}}\Sigma^{-1}\frac{\partial\Sigma}{\partial\theta_{k}}\left(\mathbf{y}-\mu\right) \tag{6}$$

With the right values of hyperparameters we now can write the joint distribution of known function values of the training cases (f) and set of function values (f_*) corresponding to the test input set. The joint distribution is expressed as (7) where $\mu=m(x_i),\ i=1,...,n$ and test mean μ_* [8]. The training set covariance is written as Σ, training-test set covariances as Σ_*, and test set covariance Σ_{**}.

$$\begin{bmatrix}\mathbf{f}\\ \mathbf{f}_*\end{bmatrix}\sim\mathrm{N}\left(\begin{bmatrix}\mu\\ \mu_*\end{bmatrix},\begin{bmatrix}\Sigma & \Sigma_*\\ \Sigma_* & \Sigma_{**}\end{bmatrix}\right) \tag{7}$$

Because values for the training set $\mathbf{f}$ is known we can focus on the conditional distribution of $\mathbf{f}_*$ given $\mathbf{f}$ which is also the posterior distribution for the test set. The posterior distribution can be shown as (8). After training the Gaussian process using the past wind power data as training set we can generate the near future wind power mean function and covariance function. Fig. 2 shows one hour ahead forecasting results. Train set is expressed with the black solid line, forecast results with red dotted line, and ground truth with the blue solid line. The grey area shows the 68% confidence interval using σ value as one.

$$\mathbf{f}_*|\mathbf{f}\sim\mathrm{N}\left(\mu_*+\Sigma_*^{T}\Sigma^{-1}\left(\mathbf{f}-\mu\right),\Sigma_{**}-\Sigma_*^{T}\Sigma^{-1}\Sigma_*\right) \tag{8}$$

2.2 Used Data

For Gaussian process input data we chose one of the wind turbine outputs provided by ERCOT. The data was preprocessed to provide one actual measurements every one hour. The points for all readings are aligned in time with UTC stamped.

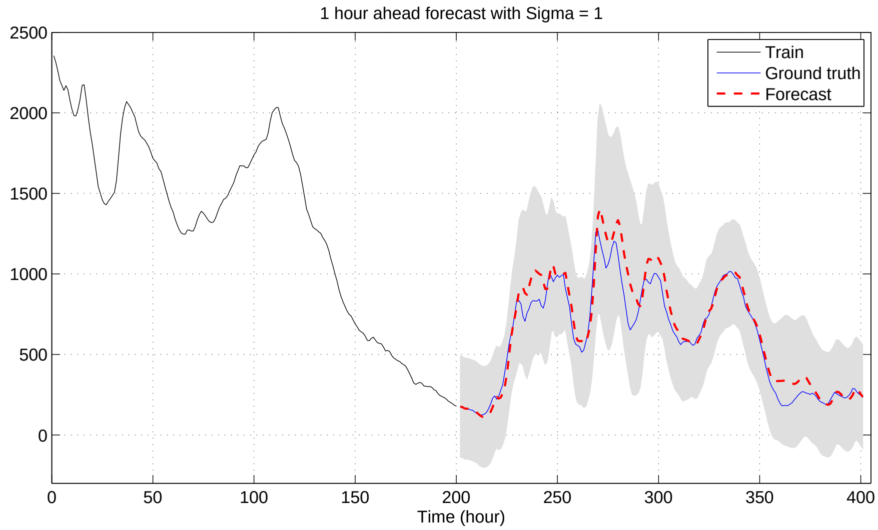


Figure 1: One hour ahead forecast results.

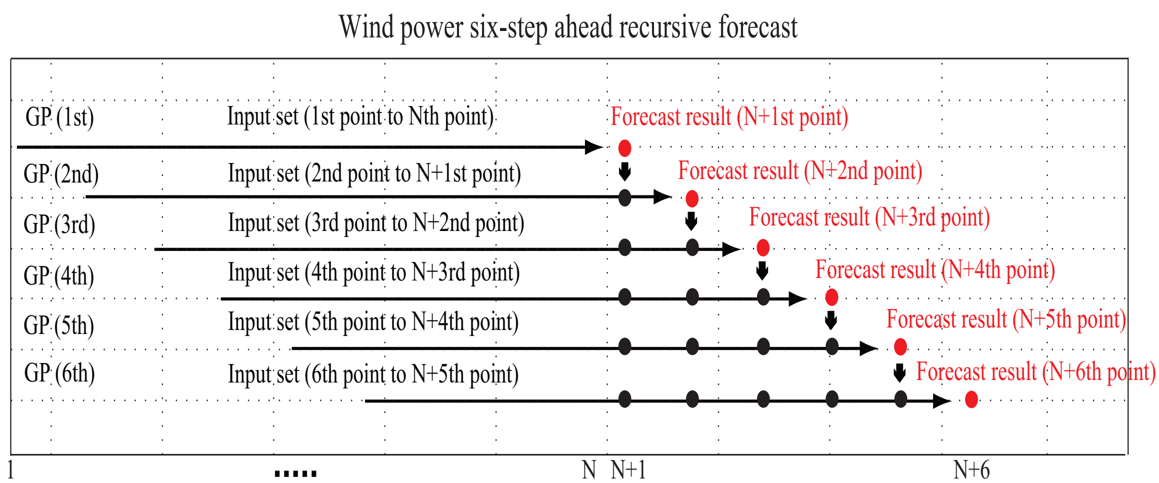


Figure 2: Gaussian process training and forecasting wind power.

2.3 Wind power recursive forecast simulation

For each given wind power recursive forecast was processed for multi-stage problem purpose. By using six-step recursive forecast we were able to anticipate the relationship between the net production and wind power output for six steps ahead from the given wind power. Fig. 2 shows the forecasting process. For each simulation, Gaussian process was trained with wind data matrix which was matched with matrix that contained wind data of one step (hour) later. After Gaussian processed was trained we were able to generate a one step ahead forecasted result by plugging in test set. Forecasted result was used as a test set to produce the next step forecasted result, which was two steps ahead from the initial test set. This process was repeated to create six steps ahead forecast results. A sample of simulation results is provided in Fig. 3.

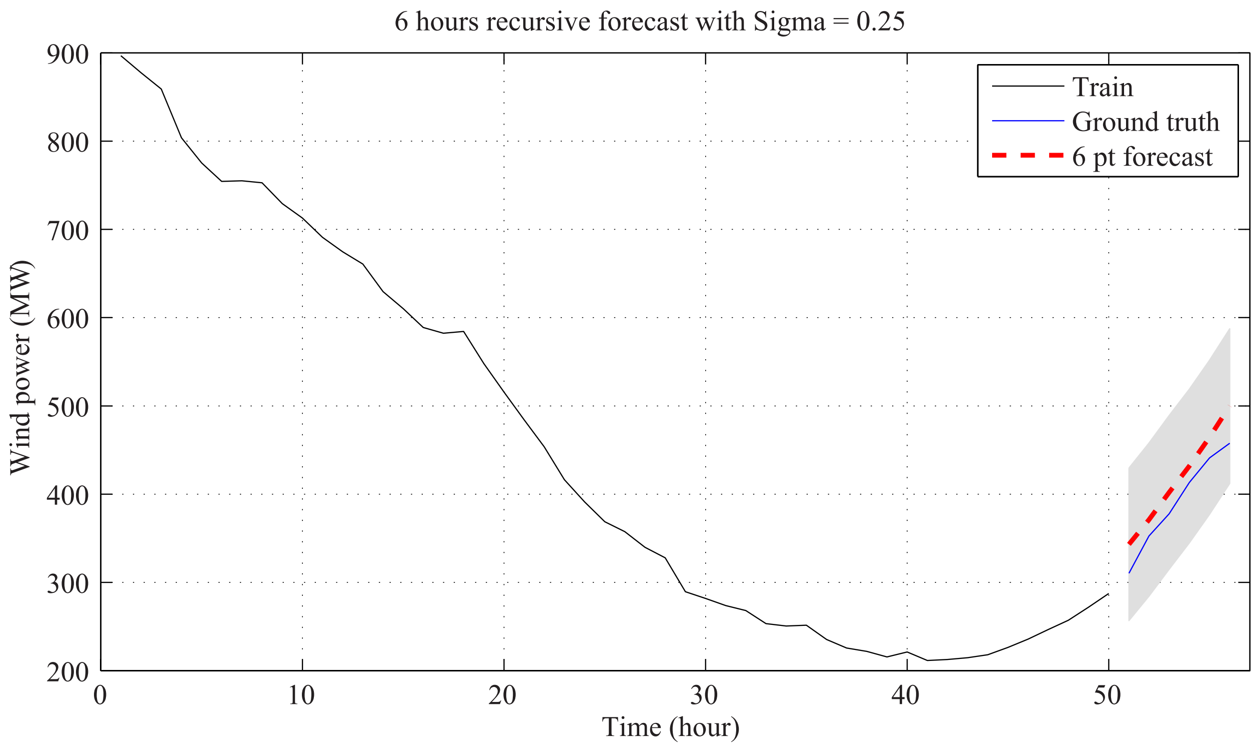


Figure 3: Six hour ahead recursive forecast result.

3 Storage system modeling

A storage device is assumed to be a lead-acid storage. However, accomplishment in this paper may be applied to all storage device based applications. The storage system model need to consider five parameters which are power rating, storage capacity, state of charge (SOC) level, discharging, and charging.

3.1 Storage Parameters

1. Power rating (PR) $[MW]$: It represents the output power rating of a storage.

2. storage capacity $[MWh]$: It represents a maximum exchangeable energy that can be charged or discharged.

3. State of charge (SOC) level $[MWh]$: It represents the level of charged energy with respect to the storage capacity.

4. Discharge (Q_t^D) $[MW]$: It represents the amount of storage discharged.

5. Charge (Q_t^C) $[MW]$: It represents the amount of storage charged.

We assume that charging and discharging operation of the storage do not take place at the same time. Charging and discharging parameters have been separated because a storage has different efficiency for charging and discharging. The operation of the storage system model depends on both net product and wind power. The relationship between the previous net production and current wind power is classified into four different cases by their power difference. According to these four cases, the penalty function can be classified by four segments by their power difference. Since the power difference is represented by four different ranges of storage operations, the penalty function can also be classified into four segments by the storage operation. As a result, since the penalty function is a piecewise convex function, the total output of penalty function becomes the objective function, and the four segments are represented as four inequality constraints. In addition to the objective function, other constraints related to storage operations are included.

The time line of a storage operation is shown in steps.

1. At any given time t, initial Net production N_t, wind power output W_t, and the SOC level SOC_t are given.
2. The wind power output W_{t+1} at the next one hour is generated.
3. Based on the forecasted result, recursive forecasts are conducted to generate the next six possible wind power outputs $W_{t+2}, W_{t+3}, W_{t+4}, W_{t+5}, W_{t+6}$, and W_{t+7} that will show us the possible future trend of wind power.
4. After running the optimization process, the optimal storage operation Q_{t+1} at time $t+1$ will be decided.
5. This process will be repeated in the next time step.

The operation time line is shown in Fig. 4.

3.2 Storage system model with loss and round-trip efficiency

Round-trip efficiency is the gain of charged energy which is expressed by e. Since we can only measure the round-trip efficiency, the losses for one time charging and discharging are defined as the square root of the round-trip efficiency and its inverse respectively shown by (9). Operation time interval is written as T_{INT} which is set as 60 minutes in this paper. It should be noted that the unit conversion coefficient $T_{INT}/60$ is used since the unit of the SOC is [MWh], and the unit of Q^D and Q^C is [MW].

$$SOC_{t+1} = SOC_t - (Q^D_{t+1} \times \frac{1}{\sqrt{e}} - Q^C_{t+1} \times \sqrt{e}) \times \frac{T_{INT}}{60} \tag{9}$$

Furthermore, the storage is generally not fully charged because its internal resistance. It is assumed that a storage can be charged up to 90% of its capacity, and it can be discharged only down to 10% of its capacity.

4 Nomenclature

This section summarizes the notation used in the development of the model. Without loss of generality, we assume that each bus has exactly one generator and one load in order to simplify the presentation of the model. Also, wind

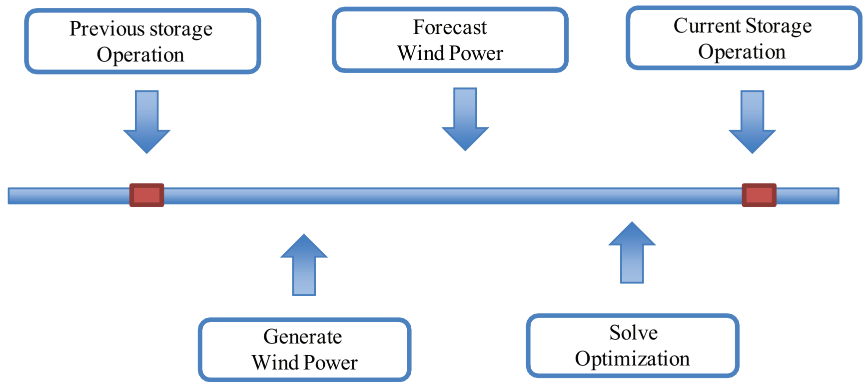


Figure 4: Time Line of storage operation.

power is modeled as negative load in our formulation and "net generation" is defined as wind power output minus storage charge or discharge amount.

Indices and Index Sets:

$t \in T$ Time $\{0, ..., T\}$

Parameters (units):

a Slope of penalty cost within the ramp rate limits $(US\$/MWh)$

b Slope of penalty cost out of the ramp rate limits $(US\$/MWh)$

c Penalty cost of storage operation $(US\$/MWh)$

e Efficiency of charging storage

S storage capacity (MWh)

PR storage power rating (MW)

PR^D storage discharging power rating (MW)

PR^C storage charging power rating (MW)

T_{int} Operation time interval (min)

SOC_t Level of charged energy with respect to the storage capacity (MWh)

R_u Ramp-up bound (MW)

R_d Ramp-down bound (MW)

$N_t - R_d$ Ramp-down constraint (MW)

$N_t + R_u$ Ramp-up constraint (MW)

W_t Wind power generation (MW)

N_0 Initial net generation (MW)

Decision Variables (Units):

N_t Net generation (MW)

Q_t Amount of storage charge or discharge (MW)

Q_t^{Di} Amount of storage discharge (MW)

Q_t^{Ci} Amount of storage charge (MW)

Z_t Penalty cost $(US\$/MWh)$

5 Storage Operation Framework

5.1 Objective Function

Objective function differs by the relationship between net productions and forecasted wind powers which is explained in the next subsections. Also, the objective function is reset based on the calculated storage operation until the optimized operation value is reached. For example, if we are given the current net production N_t and next wind power W_{t+1} then can we set this W_{t+1} to be the initial net production as N_{t+1} because storage operation value at $t+1$ is unknown. Next, initial objective function is set and solved by using linear programming based on six forecasted wind power $(W_{t+2}, W_{t+3}, W_{t+4}, W_{t+5}, W_{t+6}$, and $W_{t+7})$. The solution produces the storage operation at $t+1$ and the net production N_{t+1}, which gives us a new objective function. This process is repeated until an optimum net production value is reached.

5.2 Violating Upper Ramp Limit

Suppose the wind power W_{t+1} blows more than the ramp-up limit:

$$N_t + R_u \le W_{t+1} \tag{10}$$

The relationship between the ramp-up limit $N_t + R_u$ and wind power W_{t+1} is shown in Fig. 5(a) with sample values; N_t is 80 MW, R_u is 10 MW, and W_{t+1} is 100 MW. In this case, according to the storage operation Q_{t+1}, there are three possible cases, which are

$$\begin{aligned} N_t + R_u &\le W_{t+1} + Q_{t+1} \\ N_t - R_d \le W_{t+1} &+ Q_{t+1} < N_t + R_u \\ W_{t+1} &+ Q_{t+1} < N_t - R_d \end{aligned} \tag{11}$$

The ranges of three cases are well shown in Fig. 5(b).

The cost function Z_{t+1} is defined differently by three ranges. For the first case, the cost function Z^1_{t+1} is defined as

$$Z^1_{t+1} = |W_{t+1} + Q_{t+1} - N_t - R_u| \times b \tag{12}$$

For the second case, the cost function Z^2_{t+1} is defined as

$$Z^2_{t+1} = |W_{t+1} + Q_{t+1} - N_t - R_u| \times a \tag{13}$$

For the third case, the cost function Z^3_{t+1} is defined as

$$Z^3_{t+1} = |W_{t+1} + Q_{t+1} - N_t + R_d| \times b \tag{14}$$

As a result, the cost function Z_{t+1} considering all three cases are defined as:

$$\begin{aligned} Z_{t+1} = {} & u(W_{t+1} + Q_{t+1} - N_t - R_u) \times |W_{t+1} + Q_{t+1} - N_t - R_u| \times b \\ & + [u(W_{t+1} + Q_{t+1} - N_t + R_d) - u(W_{t+1} + Q_{t+1} - N_t - R_u)] \\ & \times |W_{t+1} + Q_{t+1} - N_t - R_u| \times a \\ & + u(-W_{t+1} - Q_{t+1} + N_t - R_d) \times |W_{t+1} + Q_{t+1} - N_t + R_d| \times b \end{aligned} \tag{15}$$

where $u(x)$ is the unit step function, which is defined as

$$u(x) = \begin{cases} 1, & \text{if } x \ge 0 \\ 0, & \text{if } x < 0. \end{cases} \tag{16}$$

The a is the slope of the cost function between the upper ramp limit and lower ramp limit, and the b is the slope of the cost function out of the upper ramp limit and lower ramp limit.

When the wind violates the upper ramp limit, the objective function is designed to select the storage operation which drives the net production N_{t+1} to the ramp-up limit. Since wind has a trend, ramp-up event will follow the ramp-up event with the high probability. Therefore, there is no reason to absorb power more than the power difference between the wind power W_{t+1} and upper ramp limit.

The cost function Z_{t+1} in (15) can be rewritten as a function of the storage operation Q_{t+1} as

$$Z_{t+1} = \begin{cases} b \times (Q_{t+1} + W_{t+1} - N_t - R_u) \\ -a \times (Q_{t+1} + W_{t+1} - N_t - R_u) \\ -b \times (Q_{t+1} + W_{t+1} - N_t + R_u) + a \times (R_d + R_u) \end{cases} \tag{17}$$

The conditions of Q_{t+1} are given as

$$if \begin{cases} N_t - W_{t+1} + R_u \leq Q_{t+1} \\ N_t - W_{t+1} - R_d \leq Q_{t+1} < N_t - W_{t+1} + R_u \\ Q_{t+1} < N_t - W_{t+1} - R_d \end{cases} \tag{18}$$

All three ramp functions are plotted in Fig. 5(c) with respected to the storage operation.

Since the cost function Z_{t+1} is the piecewise convex function, it can be represented as

$$\begin{aligned} & \min_{Q_{t+1}} Z_{t+1} + c \times |Q_{t+1}| \\ \text{subject to } & Z_{t+1} \geq \quad b \times (Q_{t+1} + W_{t+1} - N_t - R_u) \\ & Z_{t+1} \geq -a \times (Q_{t+1} + W_{t+1} - N_t - R_u) \\ & Z_{t+1} \geq -b \times (Q_{t+1} + W_{t+1} - N_t + R_d) + a \times (R_d + R_u) \end{aligned} \tag{19}$$

where $c \times |Q_{t+1}|$ is added to have complementary values of Q^D_{t+1} and Q^C_{t+1}.

5.3 Between the ramp-up limit and the ramp-down limit

Suppose the wind power W_{t+1} blows between the ramp-up limit and the ramp-down limit. In this case, the objective function should be designed to let the wind blow without a storage operation since wind is within ramp limits. However, according to the forecasted wind power output, the storage will operate within the ramp limits.

In a similar way in the previous subsection, according to the storage operation Q_{t+1}, there are four cases, which are

$$\begin{aligned} N_t + R_u &\leq W_{t+1} + Q_{t+1} \\ W_{t+1} &\leq W_{t+1} + Q_{t+1} < N_t + R_u \\ N_t - R_d &\leq W_{t+1} + Q_{t+1} < W_{t+1} \\ & \quad W_{t+1} + Q_{t+1} < N_t - R_d \end{aligned} \tag{20}$$

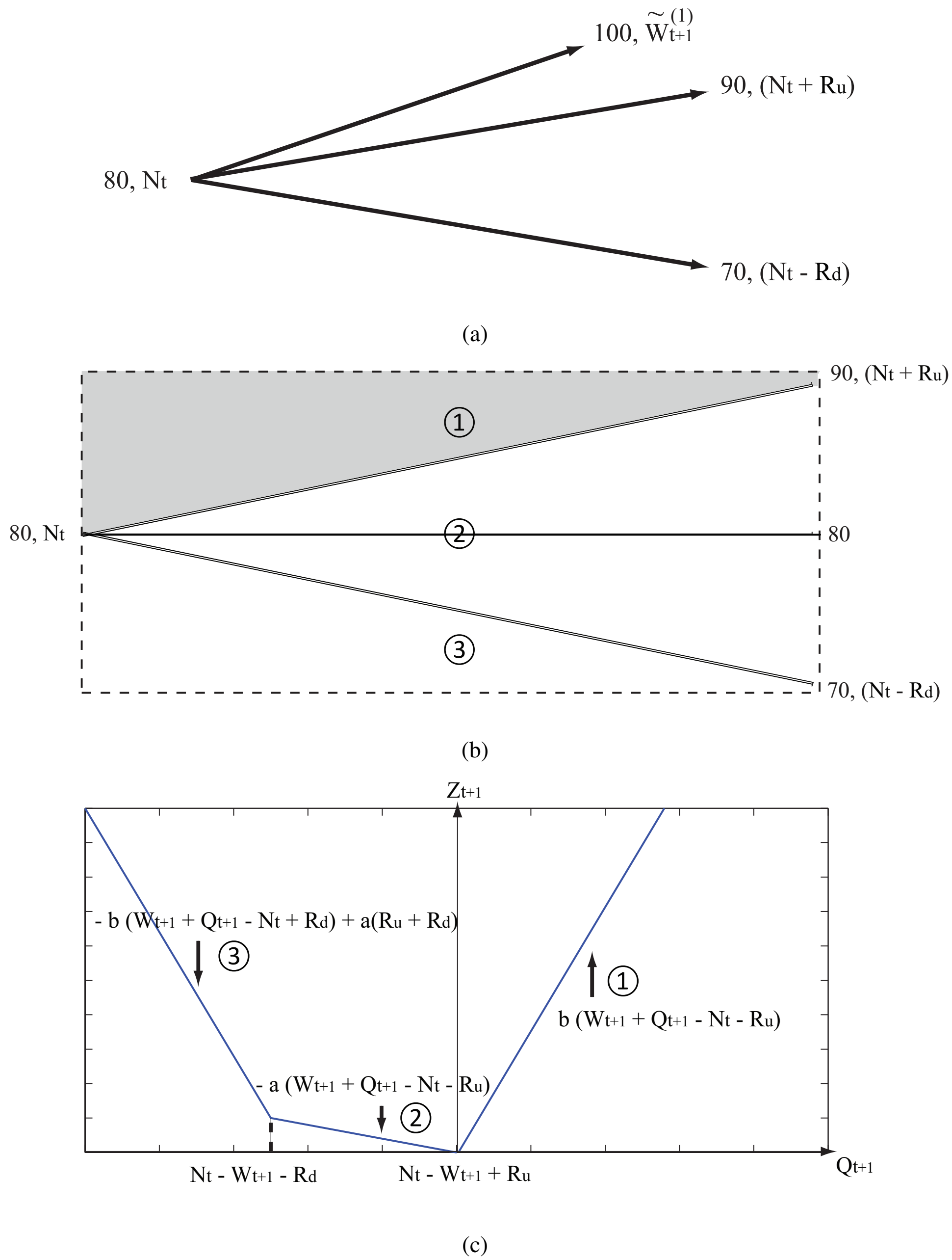


Figure 5: (a) Wind blows more than the ramp-up limit. (b) Three possible ranges of the net production at the next step N_{t+1}. (c) Objective functions with respect to ranges of storage operation Q_{t+1}.

The cost function Z_{t+1} is defined differently by four cases. For the first case, the cost function Z^1_{t+1} is defined as

$$Z^1_{t+1} = |W_{t+1} + Q_{t+1} - N_t - R_u| \times b \tag{21}$$

For the second case, the cost function Z^2_{t+1} is defined as

$$Z^2_{t+1} = |Q_{t+1}| \times a \tag{22}$$

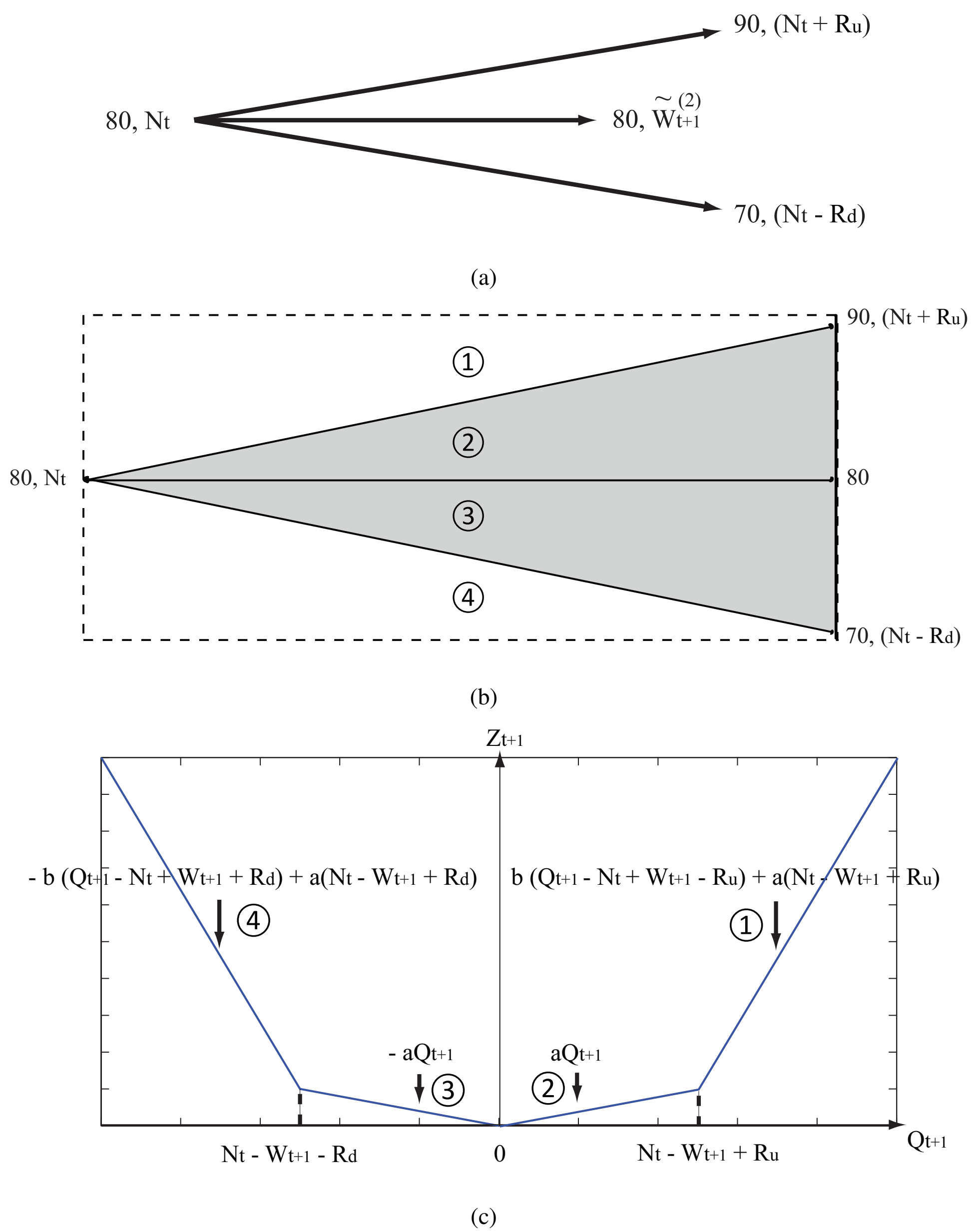


Figure 6: (a) Wind blows within the ramp limits. (b) Three possible ranges of the net production at the next step N_{t+1}. (c) Objective functions with respect to ranges of storage operation Q_{t+1}.

For the third case, the cost function Z^3_{t+1} is defined as

$$Z^2_{t+1} = |Q_{t+1}| \times a \tag{23}$$

For the fourth case, the cost function Z^4_{t+1} is defined as

$$Z^3_{t+1} = |W_{t+1} + Q_{t+1} - N_t + R_d| \times b \tag{24}$$

As a result, the cost function Z_{t+1} considering all four cases are defined as:

$$\begin{aligned}
Z_{t+1} = {} & u(W_{t+1} + Q_{t+1} - N_t - R_u) \times |W_{t+1} + Q_{t+1} - N_t - R_u| \times b \\
& + [u(W_{t+1} + Q_{t+1} - W_{t+1}) - u(W_{t+1} + Q_{t+1} - N_t - R_u)] \\
& \times |W_{t+1} + Q_{t+1} - W_{t+1}| \times a \\
& + [u(W_{t+1} + Q_{t+1} - N_t + R_d) - u(W_{t+1} + Q_{t+1} - W_{t+1})] \\
& \times |W_{t+1} + Q_{t+1} - W_{t+1}| \times a \\
& + u(-W_{t+1} - Q_{t+1} + N_t - R_d) \times |W_{t+1} + Q_{t+1} - N_t + R_d| \times b
\end{aligned} \tag{25}$$

The cost function Z_{t+1} in 25 can be rewritten as a function of the storage operation Q_{t+1} as

$$Z_{t+1} = \begin{cases} b \times (W_{t+1} + Q_{t+1} - N_t - R_u) - a \times (W_{t+1} - N_t - R_u) \\ a \times Q_{t+1} \\ -a \times Q_{t+1} \\ -b \times (W_{t+1} + Q_{t+1} - N_t + R_d) - a \times (W_{t+1} - N_t + R_d) \end{cases} \tag{26}$$

The conditions of Q_{t+1} are given as

$$if \begin{cases} N_t - W_{t+1} + R_u \leq Q_{t+1} \\ 0 \leq Q_{t+1} < N_t - W_{t+1} + R_u \\ N_t - W_{t+1} - R_d \leq Q_{t+1} < 0 \\ Q_{t+1} < N_t - W_{t+1} - R_d \end{cases} \tag{27}$$

Since the cost function Z_{t+1} is the piecewise convex function, it can be represented as

$$\begin{aligned}
& \min_{Q_{t+1}} Z_{t+1} + c \times |Q_{t+1}| \\
& \text{subject to} \\
& Z_{t+1} \geq b \times (W_{t+1} + Q_{t+1} - N_t - R_u) - a \times (W_{t+1} - N_t - R_u) \\
& Z_{t+1} \geq a \times Q_{t+1} \\
& Z_{t+1} \geq -a \times Q_{t+1} \\
& Z_{t+1} \geq -b \times (W_{t+1} + Q_{t+1} - N_t + R_d) - a \times (W_{t+1} - N_t + R_d)
\end{aligned} \tag{28}$$

5.4 Violating ramp-down Limit

When wind violates the ramp-down limit, the range of wind is as follows.

$$W_{t+1} \leq N_t - R_d \tag{29}$$

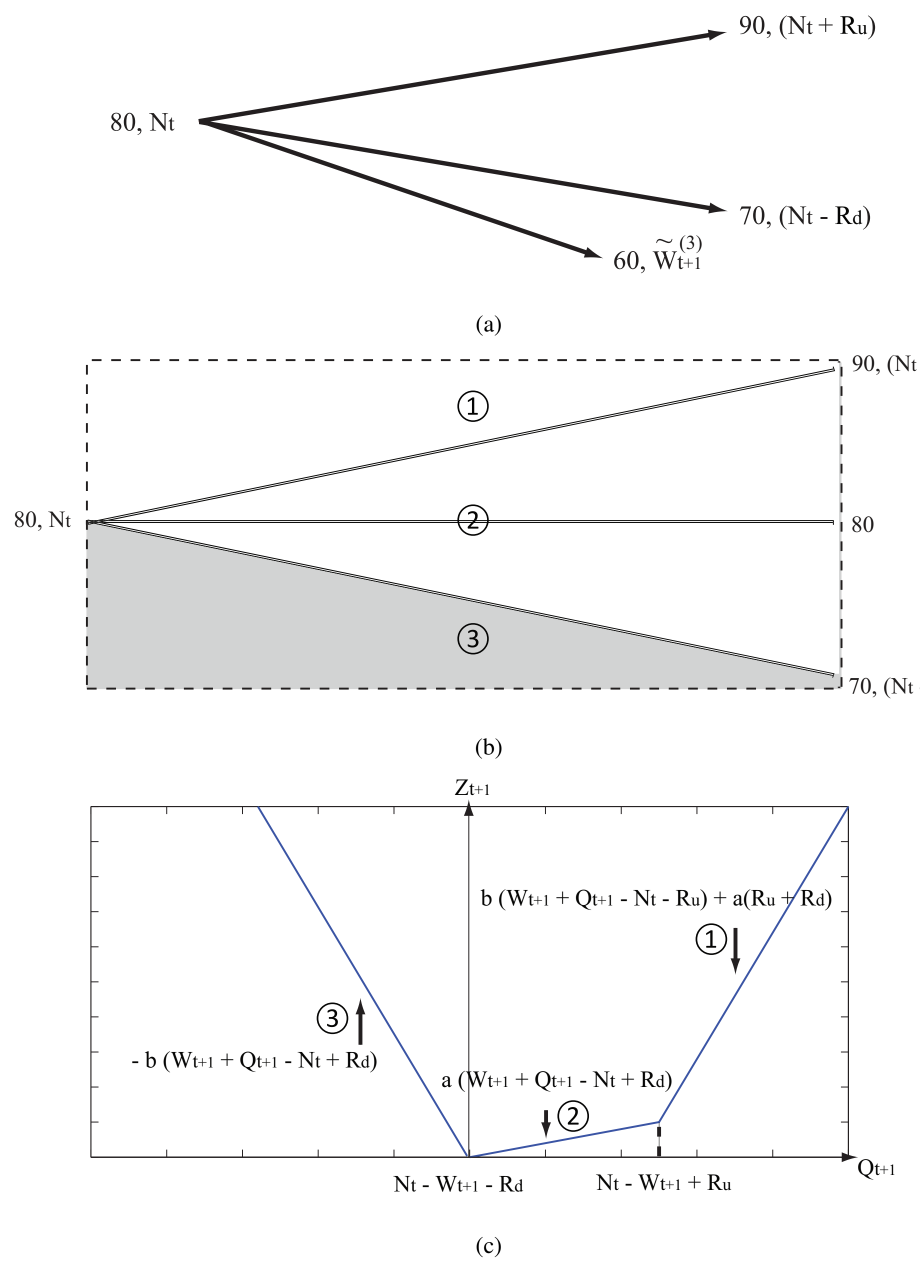


Figure 7: (a) Wind blows less than the ramp-down limit. (b) Three possible ranges of the net production at the next step N_{t+1}. (c) Objective functions with respect to ranges of storage operation Q_{t+1}.

In this ranges, the cost function can be defined as by following processes mentioned above

$$
\begin{aligned}
&\min_{Q_{t+1}} Z_{t+1} + c \times |Q_{t+1}| \\
\text{subject to } Z_{t+1} &\geq \quad b \times (Q_{t+1} + W_{t+1} - N_t - R_u) + a \times (R_d + R_u) \\
Z_{t+1} &\geq \quad a \times (Q_{t+1} + W_{t+1} - N_t + R_d) \\
Z_{t+1} &\geq -b \times (Q_{t+1} + W_{t+1} - N_t + R_d)
\end{aligned}
\tag{30}
$$

6 Results and analysis

6.1 Simulation

Simulation conditions were set as shown below. Three different values of the initial SOC level was tested: 0.9 of the storage size, 0.3 of the storage size, and 0.1 of the storage size.

- a=0.1
- b=1
- Storage Size = 500 MWh
- Discharging Power Rating: 50 MW
- Charging Power Rating: 50 MW
- Initial Storage Size: 250 MWh
- Operation Time Interval: 60 min
- Data Sampling Period: 60 Min
- Operation number: 20 step
- Recursive forecast setting: 6 steps ahead
- Minimum SOC Level: 0.1 to the storage size
- Maximum SOC Level: 0.9 to the storage size
- Initial SOC Level: (1) 0.9 to the storage size. (2) 0.3 to the storage size. (3) 0.1 to the storage size.
- The round trip efficiency: 0.9
- Ramp-up Limit: 10 MW/Min
- Ramp-down Limit: 10 MW/Min

6.2 Initial SOC level case (1) results

A battery system is simulated using the given simulation conditions. Initial SOC level was set as 0.9 to the storage size which was the maximum SOC level the battery can store. Simulation results are shown in Fig. 8(a). The blue solid line shows the wind power, and the black solid line expresses the optimal case of net production when no battery size nor power rating limits are considered. The red dotted line shows the net production solved by using linear programming considering the battery constraints. Since the battery starts with the highest amount of SOC level the net production follows the optimal case until 18th step. After the 18th step the wind power exceeds the ramp up limit by more than the battery's power rating (50 MW). This is when the battery starts charging, but the battery can only charge up to 50 MW each hour. Therefore, beyond 18th step the net production follows the wind power line with the gap of 50 MW, which indicates that the battery is charging 50 MW each hour. The results of other cases (2) and (3) are put together with case (1) in Fig. 8 in order to easily compare the different battery operations according to the initial SOC levels.

6.3 Initial SOC level case (2) results

For the second simulation, initial SOC level was set as 0.3 to the storage size. Rest of the simulation conditions stayed the same. Simulation results are shown in Fig. 8(b). In Fig. 8(b) the net production follows the optimal case until the 13th step. However, after 14th step the net production drops down and merge with wind power line because the battery is depleted down to the minimum at 14th step. As the wind power curves up at 17th step all lines merge together, and after 18th step the battery operates the same as case (1). Fig. 9 shows the battery operation and SOC level with regard to the wind power and net production.

6.4 Initial SOC level case (3) results

The initial SOC level was set as the minimum storage size (0.1 to the storage size). Simulation results are shown in Fig. 8(c). For this case no discharge can be made until the wind power charges up the battery. Since the wind power does not increase until 18th step net production follows the wind power line completely until step 17.

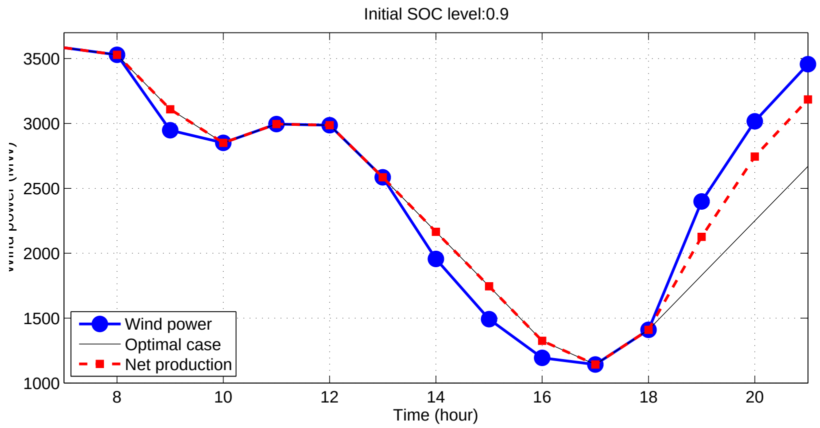
7 Conclusion

This section summarizes this paper and suggest future works.

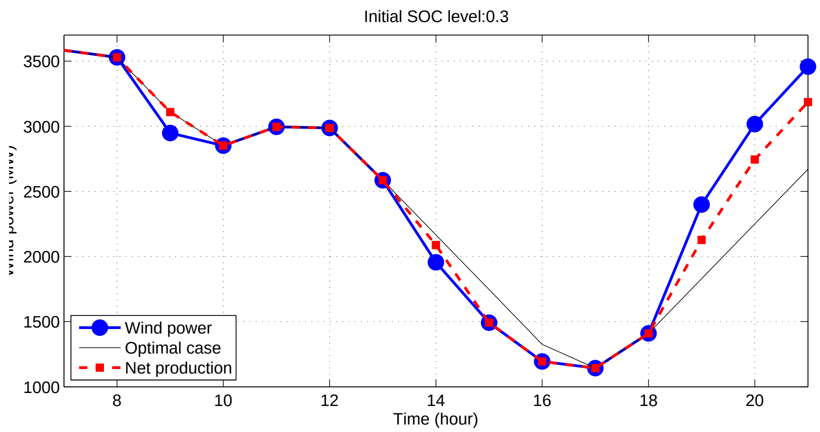
7.1 Summary

1. In order to respond to large ramp-up or down events, a battery should manage SOC level. We were able to forecast the wind power six steps ahead by using recursive Gaussian process.

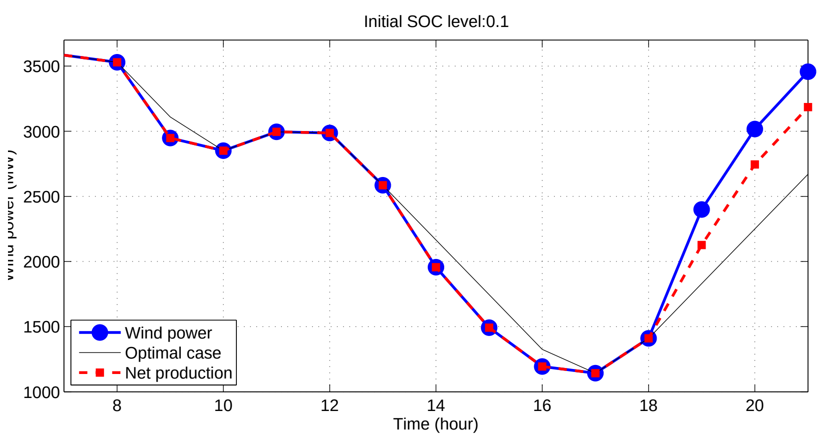
2. In order to respond to instant excursions, a battery had better follow the ramp events. For example, for a instant ramp-up event, a battery had better discharge power before a instant ramp-up event in order to reduce the ramp rate since wind power will continuously increase. On the other hand, for a instant ramp-down event, a battery had better charge power before a instant ramp-down event in order to reduce the ramp rate since wind power will continuously decrease.



(a)



(b)



(c)

Figure 8: (a) Optimized storage operation with initial 0.9 SOC level. (b) Optimized storage operation with initial 0.3 SOC level. (c) Optimized storage operation with initial 0.1 SOC level.

7.2 Future Work

1. ***Cost Analysis**:* The investment cost of a battery system should be compared to the saved penalty. Furthermore, a battery can buy energy when it is cheap, and it can sell energy when it is expensive. We can sell saved wind

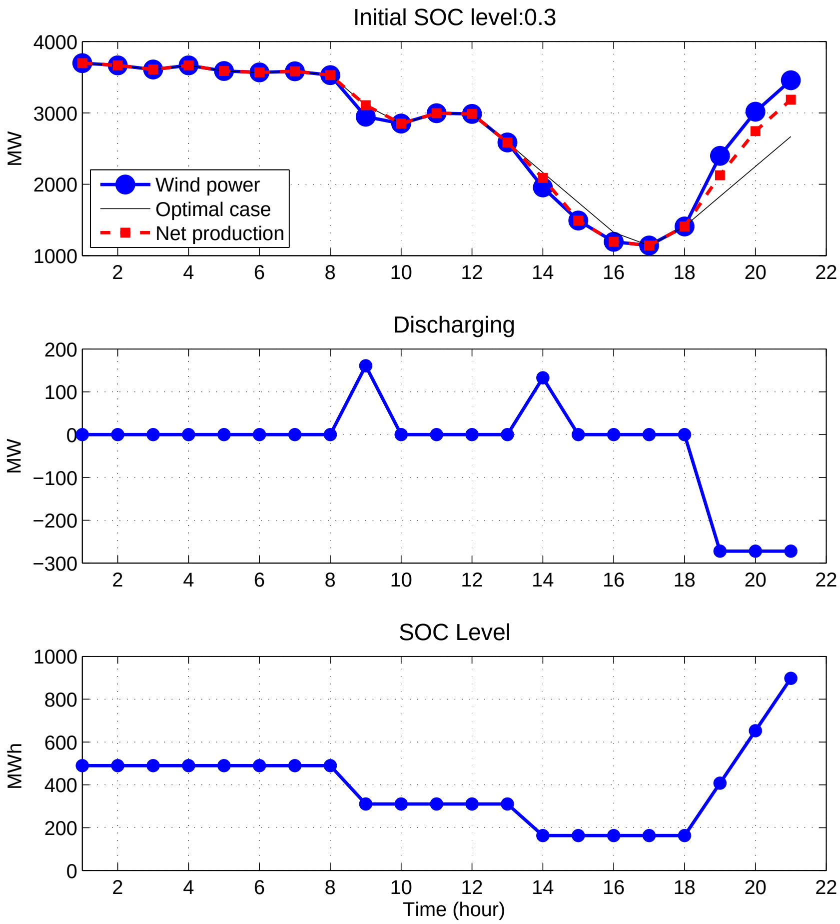


Figure 9: Battery operation and SOC level with regard to the wind power and net production.

power instead of curtailment. It will bring more profits.

2. ***Optimal Rating**:* For the given capacity of the wind farms, the optimal power rating and storage size should be decided. Those optimal values should be able to mitigate ramp rates limits violation efficiently. The optimal power rating and storage size should be decided to minimize the penalty costs based on the cost analysis.

3. ***Penalty Function**:* The suitable form of the penalty function and its parameters should be decided to reflect the present electricity market. The quadratic form might be a suitable function, since it charges more penalties for more deviations. Moreover, in NYISO, there is a penalty function only for violating ramp-up rates limit. Do we really need a penalty function for violating ramp-down rates limit?

4. ***Wave Forecasting**:* The distribution of the point forecasting is very near-sight approach. Therefore, a wind path should be forecasted with probabilistic table.

5. ***Large Scale**:* As the number of scenario increase, more variables are added to the problem. To handle many

variables, techniques to solve an optimization problem should be introduced.

6. ***Ramp Events**:* We should re-calculate the probability of ramp rates limit.

Acknowledgment

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