Stochastic Optimal Control of the Storage System to Limit Ramp Rates of Wind Power Output

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***Abstract*—The purpose of this paper is to reduce the required amounts of ancillary services, by limiting ramp rates of wind power through control of a storage system. Storage operation policies to limit the ramp rate of net production (wind + storage output) are optimized in a two-stage stochastic linear program with fixed recourse. Operation policies decide the storage operation based on the probability density function of one step ahead wind power, which is forecasted by a Gaussian process. In this optimization problem, it is assumed that a financial penalty is incurred when violating the ramp rate limit (RRL), and that the penalty is linearly proportional to the number of MW per period above or below the RRLs. The L-shaped method is used to reduce the number of constraints caused by various wind power scenarios. Then, the storage specification is determined based on minimizing the sum of the penalty costs and the investment costs of the storage system. The ultimate goal of this paper is to find the relationship between the financial penalties and the RRL.**

***Index Terms*—Gaussian process, l-shaped method, stochastic optimization, storage system, wind ramp rate.**

NOMENCLATURE: **Indices and Index Sets:**

$k \in Sce$	Wind power scenario $\{1,\ldots,K\}$.
$t \in Time$	Time $\{1,\ldots,T\}$.

Parameters (units):

a	Slope of penalty function within RRLs ($\$/\mathrm{MW}$).
b	Slope of penalty function outside of RRLs ($\$/\mathrm{MW}$).
d	Penalty cost of storage operation ($\$/\mathrm{MW}$).
E	Round trip efficiency of charging storage.
u	Maximum SOC level.
l	Minimum SOC level.
p_k	Probability for the scenario k.
Sto	Storage size (MWh).
PR	Storage power rating (MW).
T_{int}	Operation interval (Min).
SOC_t	Level of charged energy (MWh).
R_u	Ramp-up limit (MW).
R_d	Ramp-down limit (MW).
W_t	Wind power generation at time t (MW).

Decision Variables (units):

N_t	Net production (MW).
Q_t	Amount of storage operation (MW).
Q_t^D	Amount of discharge (MW).
Q_t^C	Amount of charge (MW).
Z_t	Financial penalty cost ($\$/\mathrm{MWh}$).

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I. Introduction

One of the most important issues related to wind power integration is how to mitigate the intermittency of wind power while maintaining the economic value of wind power and the system reliability. As the penetration level of wind power increases, ISOs must more frequently call upon peak-load or fast ramping generators to mitigate the intermittency of the wind power so that the power system can keep the balance of supply and demand [1]. This concern is seen in the recent simulation in [2]. The economic value of wind decreases at a very high penetration level of wind power due to the cost of using peak-load and fast ramping generators when climatic events do not allow for the full use of wind capacity. Such events further increase the electricity cost. Therefore, the required amount and cost of ancillary services (AS) will increase as the penetration level of wind power increases. Consequently, the two advantages of wind power-low fuel cost and carbon emissions-will be threatened.

Much literature proposes plans to directly mitigate the wind power variability or indirectly procure more flexible resources. Among these plans, we will focus on the storage system whose advantages are well introduced in [3]. Specifically, our paper discusses using the storage system to mitigate wind power variability, assuming that doing so will reduce demands on AS. This application can be classified into three approaches: capacity firming, power bridging, and regulation services. Regarding the first approach, wind capacity firming through the Vanadium Redox flow battery is proposed in [4]. It also suggests a novel power electronic interface to firm the wind power. For power bridging, the storage system is used to compensate for wind power forecast errors [5]. This utilizes the statistical characteristics of the forecast error and decides the storage specification. Third, the storage system can directly provide regulation services [6]. Particularly, in [7], many storage configurations are tested to see whether a storage system can respond to future regulation signals.

In order to use the storage system, two key factors should be examined: storage specifications and operation policies. Many researchers have suggested methodologies for sizing a storage system. In [8], the storage size to cover an error of hour-ahead predicted wind power is decided using a neural network. In [9], the storage size to compensate for the curtailed wind power is calculated through the cost-benefit analysis. In [10], the storage sizes for isolated wind-diesel power systems are estimated using stochastic optimization through a financial analysis.

In addition, a number of storage operation policies have been introduced. In [11], the ramp rate of wind power was limited through the storage system with feedback control to dispatch the wind power. In [12], the online control algorithm has two storage systems. Furthermore, two storage systems are used in parallel to firm the capacity of wind power in [13]. In this configuration, one storage system charges energy from wind farms, and the other provides the constant power to the grid.

Although many storage systems have been proposed to reduce the effects of wind power variability, there are a few shortcomings. First, the characteristics of wind power are not reflected in the storage operation. Second, storage sizing and real-time storage operation are performed separately, so the storage cost and the storage specification are not verified through the storage operation. Third, some storage sizing literature did not consider the economic cost-benefit analysis. Finally, most research focuses on limiting short-term wind power fluctuations, but extreme ramping behaviors, such as sudden wind die-offs, are a major threat to the power system [14].

Therefore, we suggest that the ramp rate of wind power be limited to reduce the cost of AS. Since capacity firming requires large storage sizes, limiting ramp rates may be the most cost-effective application, since it can be achieved with modest storage size. Besides, in order for peak-load generators to cover the variability of wind power, the ramp rates should be limited to the ramping capabilities of the load following generators. Ramp-up rates are generally limited by wind power curtailment, and ramp-down rates are supported by reserve services. However, curtailment leads directly to a loss of profit for wind farm stakeholders. Commercial storage applications already limit ramp rates of wind power through a storage system. For example, Xtreme Power installed storage devices-a (10 MW/20 MWh) device on a 21 MW wind farm in Maui, Hawaii and a (15 MW/10 MWh) device on a 30 MW wind farm in Oahu, Hawaii-to provide ramp rate control [15]. The ramp rate limit (RRL) was $\pm 1\ \mathrm{MW/min}$ at both sites. Reference [15] claimed that the installed storage increases the wind farm owner's annual revenues by $\$243.4$ million. In [16], ramp rates of wind power were also limited in real-time operation by analyzing the distribution of ramp rates. However, there are shortcomings when a storage system limits the ramp rate using a deterministic control policy: a) If RRLs are strictly obeyed, a huge power rating and storage size are required; b) When RRLs need to be violated, it is hard to decide an acceptable violation; c) There is ambiguity when deciding the optimal storage operation when the wind blows within the RRLs; and d) A storage system without forecasting information has a shortsighted operation.

Therefore, to compensate for the shortcomings of deterministic control policies, we design a real-time storage system controlled through a stochastic optimization process and wind power forecasting. To apply the optimization scheme, it is assumed that there is a financial penalty for deviating outside the RRLs, and that the penalty is linearly proportional to the number of MW per period above or below the RRLs, so that deviation from the RRLs is allowed at a cost. The actual ramp rate penalty varies according to different independent system operators (ISO)s. According to [17], ERCOT does not penalize wind generation resources for under generation but penalizes for over generation only if their actual output is 10% greater than their dispatch instructions per minute [18]. However, at a high penetration level of wind power, even peaking generators that have high ramp rates cannot quickly cover sudden wind die-offs. Therefore, penalties for under generation should be harsh. Over generation should also be penalized harshly because if many wind farms ramp up at the same time, even at a seemingly low level of 10%, their collective impact on the power system would be too great to handle. In some systems, the ramp rate penalty might be very high, reflecting that violating the ramp rate results in a highly unsatisfactory condition, such as loss of load. However, we will assume penalties that are more modest than these other systems but harsher than ERCOT's.

Under these assumptions, storage operation policies are decided by solving a two-stage stochastic linear problem with fixed recourse to minimize the financial penalty. A Gaussian Process (GP) provides an estimate of the future wind power in a single step ahead and its conditional probability density function (PDF). In order to cope with many scenarios, the L-shaped method is used to reduce the number of constraints caused by increasing the number of scenarios. The scenarios are possible wind power values one step ahead. The net production performance is compared to the case of an unlimited storage system with an infinite power rating and storage size. It is also compared to deterministic operation, and it is shown that the storage operation with forecasts outperforms the storage operation without forecasts. Furthermore, much literature has researched the effectiveness of storage for improving the short-term wind power variability, by focusing on capacity firming. However, since we will focus on limiting ramp rates instead of capacity firming, we can also limit the long-term variability by sequentially limiting short-term variability. Setting the operation time at one minute means that short term variability is more efficiently controlled and that long term variability is also controlled to some extent by sequentially limiting short term variability.

Our ultimate goal is to decide the optimal storage specifications that minimize the sum of the storage investment cost and the financial penalties incurred through ramp rate violations. In addition, the relationship between the penalty cost and storage cost will be analyzed.

The paper is organized as follows. Section II analyzes the relationship between the ramp rate and AS. In Section III, wind power is forecasted through the GP. Section IV explains the mechanism of the storage system, and the optimization framework for the storage operation is described. Then, Section V estimates the storage specification, clarifies the relationship between the penalty and RRLs, and presents quantitative results. Finally, Section VI presents a summary with concluding remarks and future works.

II. Ramp Rate & Ancillary Services

In this section, the ramp rate and wind power variability are defined. Then, the relationship between the ramp rate and amount of non-spinning reserve service (NSRS) is analyzed, and the trend of amounts of regulation services is analyzed with respect to the size of the RRLs. A ramp event is defined as the power change at every operation interval. A ramp event is classified as a ramp-up event if the power change is positive, and it is classified as a ramp-down event if the power change is negative. The ramp rate is defined as the power difference from minute to minute, and its unit is $[\mathrm{MW}/\mathrm{min}]$. There are two types of ramp rates: ramp-up rate and ramp-down rate, and there are ramp limits for each. It is worth noting that the ramp-up event has a positive ramp rate, and the ramp-down event has a negative ramp rate. The variability is defined as the standard deviation of the minute to minute difference between wind power outputs [19].

A. Non-Spinning Reserve Service

We will follow ERCOT methodologies for determining the NSRS and show that limiting ramp rates of wind power can reduce the amount of the NSRS. The NSRS requirements linearly depend on three important data sets [20]. First, the 95th percentile of net load uncertainty for the target month and for the same month in the previous year is required. Second, the average regulation up requirement for the target month is needed. Third, the average net load uncertainty should be calculated. We estimate the 95th percentile of net load uncertainty as a function of the RRLs because the amounts of NSRS are linearly proportional to net load forecasting errors [21]. The net load is defined as the load minus the wind power, and the uncertainty is defined as the measured values minus the forecast values. It is worth noting that the 95th percentile value is calculated for each four hour block. In our application, we use 6th block in off-peak hours, which starts from 18:00 to 22:00 when wind blows stronger than other hour blocks.

Fig. 1 shows the change of the 95th percentile of net load uncertainty as the RRLs are relaxed. Wind power was sampled on July, 2010. The load data, load forecasting, and wind power forecasts are measured at every hour by ERCOT. Forecasted values are issued at 16:00 in the day-ahead. Ramp rates are limited by an unlimited storage system whose power rating and storage size are infinite. We can see that the uncertainty increases as the RRLs are increased. Therefore, we can carefully say that limiting ramp rates can reduce the required amounts of the NSRS.

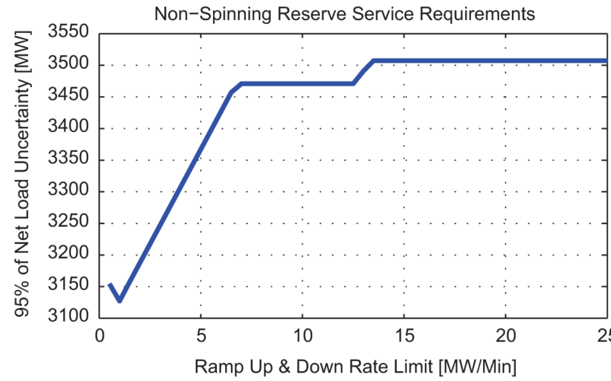

Fig. 1. The change of 95% net load uncertainty is plotted against the ramp rate limit. As RRLs are relaxed, the uncertainty increases. Ramp up and down rates are the same.

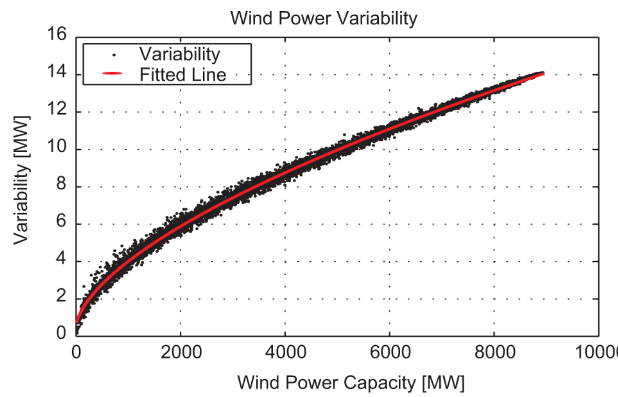

Fig. 2. The variability is plotted against the total wind power capacity. The red dot follows the exponential curve, $y = ax^b + c$, where a=0.0496, b=0.6165, and c=0.4954. Furthermore, R^2 is 0.9965.

B. Regulation Service Requirements

The relationship between ramp rates and amount of regulation services is also analyzed. In Fig. 2, the variability is plotted against the total wind power capacity. Seventy-five wind farms are used to plot the figure. The number of interconnected wind farms increases from two to 75. For the given number of wind farms, 300 combinations of wind farm interconnections are tested. The black dots represent the variability of each combination, and the red line is fitted to the variability. Fig. 2 shows that the variability increases as the wind power capacity increases with the same geographical distribution. According to [22], the amount of regulation services increases as the variability increases, so the amount of regulation services increases as the wind power capacity increases. However, limiting ramp rates will reduce the variability since the variability is the standard deviation of ramp rates. Therefore, we cautiously say that limiting ramp rates will also reduce the amount of regulation services.

III. Gaussian Process

In this section, after the GP is briefly explained, the wind power is forecasted. In this analysis, numerical weather prediction is not considered since analyzing time series data is sufficient to forecast the short-term wind power. Furthermore, the time series analysis is faster than the NWP to support the short-term storage operation interval.

A. Introduction to the Gaussian Processes

The GP has been used as a tool for the regression and classification in the fields of neuroscience, computer science, and geoscience. The GP has two important assumptions. The first one is that target values are observed with additive Gaussian noise. The second one is that outputs of a system follow a multivariate Gaussian (MVG) distribution, which is defined by the mean and covariance. The distribution of the MVG will be decided by $\mathcal{N}(\mu, \Sigma)$, where μ is the mean, and Σ is the covariance. In our application, means of MVG distribution are observed wind power outputs [23].

The MVG's covariance function is decided by the Gram matrix $\mathbf{K}$, whose elements are the inner product of two basis functions of different pairwise input vectors. In this process, input vectors are transformed by the basis functions, and target values are the linear combinations of the basis functions. We should bear in mind that our goal is to estimate the distribution of future target values conditioned on observed data. Further investigation is required to see whether the performance of the GP is superior to other algorithms in the wind power forecasting. However, in our application, the GP is used because it is a straightforward way to provide the distribution of forecasts and because it outperforms the persistence model.

B. Regression Analysis With Gaussian Processes

Suppose there are N vectors of historical input power $\mathbf{x}_i$ whose cross sectional dimension is D, and there are N output powers t_i, each of which is a scalar value. It is assumed that the vector of observed value $\mathbf{t} = (t_1, \ldots, t_N)^T$ has a zero mean. Consider a Bayesian linear regression function f_i at time i whose inputs are vectors of basis functions $\boldsymbol{\phi}$ of input vectors $\mathbf{x}_i = (x_1, \ldots, x_D)$ for $i \in 1, \ldots, N$. The model is defined in [24] as

$$f_i = \mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i) \tag{1}$$

where $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_M)^T$ is a vector of basis functions, $\mathbf{w} = (w_1, \ldots, w_M)^T$ is a vector of random weights with covariance $\alpha^{-1}\mathbf{I}_N$, and M is the dimension of the basis functions. Function f_i is observed as the output power t_i with an additive noise e_i

$$t_i = f_i + e_i. \tag{2}$$

Suppose that an additive noise of wind power follows an independent, identically distributed Gaussian distribution with zero mean and variance β^{-1}[25];

$$e_i \sim \mathcal{N}(0, \beta^{-1}). \tag{3}$$

Since the noise is independent for every t_i, the conditional PDF of observed values $\mathbf{t} = (t_1, \ldots, t_N)^T$ conditioned on the value of the regression functions $\mathbf{f} = (f_1, \ldots, f_N)^T$ is given as a MVG:

$$\Pr(\mathbf{t} \mid \mathbf{f}) \sim \mathcal{N}(\mathbf{f}, \beta^{-1}\mathbf{I}_N) \tag{4}$$

where $\mathbf{I_N}$ is the identity matrix of size N.

As mentioned above, $\mathbf{f}$ is assumed to follow the joint Gaussian distribution with zero mean and covariance matrix $\mathbf{K}_N$ so that

$$\Pr(\mathbf{f}) \sim \mathcal{N}(0, \mathbf{K}_N). \tag{5}$$

Since (1) can be rewritten as $\mathbf{f} = \boldsymbol{\Phi}\mathbf{w}$, $\mathbf{K}_N$ is defined as:

$$\mathrm{cov}(\mathbf{f}) = E[\mathbf{f}\mathbf{f}^T] = E[\boldsymbol{\Phi}\mathbf{w}\mathbf{w}^T\boldsymbol{\Phi}^T] = \alpha^{-1}\boldsymbol{\Phi}\boldsymbol{\Phi}^T = \mathbf{K}_N. \tag{6}$$

Elements of $\mathbf{K}_N$ are calculated as

$$K_{ij} = k(\mathbf{x}_i, \mathbf{x}_j) = \alpha^{-1}\boldsymbol{\phi}(\mathbf{x}_i)^T\boldsymbol{\phi}(\mathbf{x}_j) \tag{7}$$

where $k(\mathbf{x}_i, \mathbf{x}_j)$ is called the kernel function. It is selected to represent the similarity between components of $\mathbf{x}$ so that the more similar the data, the more correlated the outputs. Therefore, we don't have to define or find suitable function $\boldsymbol{\phi}$. As a result, without considering the weights and nonlinear basis functions, we can design the function of $\mathbf{x}$ by defining the kernel function.

This definition of similarity differs by applications. In this application, the squared-exponential covariance function is selected. It is defined in [26] as:

$$k(\mathbf{x}_i, \mathbf{x}_j) = \alpha^{-1} \exp\left(-\frac{1}{2h^2}(\mathbf{x}_i - \mathbf{x}_j)^2\right) \tag{8}$$

where h is the length scale between two input vectors. A set of hyperparameters is defined as H, which includes α, h, and β. Hyper-parameters in GP are adapted to improve the forecasting performance. Based on the Bayes' theorem, the marginal distribution of output power $\Pr(\mathbf{t})$ is defined as

$$\Pr(\mathbf{t}) = \int \Pr(\mathbf{t} \mid \mathbf{f}) \Pr(\mathbf{f}) d\mathbf{f} \sim \mathcal{N}(\mathbf{0}, \mathbf{K}_N + \beta^{-1}\mathbf{I}_N). \tag{9}$$

We want to know the $\Pr(t_{N+1} \mid \mathbf{t})$, for the given new test data $\mathbf{x}_{N+1}$. It can be factored out from the marginal distribution of $\mathbf{t}_{N+1}$ by a matrix operation. The marginal distribution is inferred from (9) by increasing the index N as:

$$\Pr(\mathbf{t}_{N+1}) \sim \mathcal{N}\left(\mathbf{0}, \mathbf{K}_{N+1} + \begin{bmatrix} \beta^{-1}I_N & \mathbf{0} \\ \mathbf{0}^T & 0 \end{bmatrix}\right) \tag{10}$$

where the noise term $\beta^{-1}\mathbf{I}_N$ is only added to the training data. $\mathbf{K}_{N+1}$ could be calculated by increasing a row and column of $\mathbf{K}_N$, so it is partitioned into:

$$\mathbf{K}_{N+1} = \begin{bmatrix} \mathbf{K}_N & \mathbf{k}_{N+1} \\ \mathbf{k}_{N+1}^T & k(\mathbf{x}_{N+1}, \mathbf{x}_{N+1}) \end{bmatrix} \tag{11}$$

where $\mathbf{k}_{N+1}$ has $k(\mathbf{x}_i, \mathbf{x}_{N+1})$ as its element for $i = 1, \ldots, N$. By following the matrix operation in [27], we can evaluate the distribution of forecasted value t_{N+1}

$$\Pr(t_{N+1} \mid \mathbf{t}) \sim \mathcal{N}\left(\begin{matrix} \mathbf{k}_{N+1}^T\mathbf{W}\mathbf{t}, \\ k(\mathbf{x}_{N+1}, \mathbf{x}_{N+1}) - \mathbf{k}_{N+1}^T\mathbf{W}\mathbf{k}_{N+1} \end{matrix}\right) \tag{12}$$

where $\mathbf{W}$ is defined as $(\mathbf{K}_N + \beta^{-1}I_N)^{-1}$.

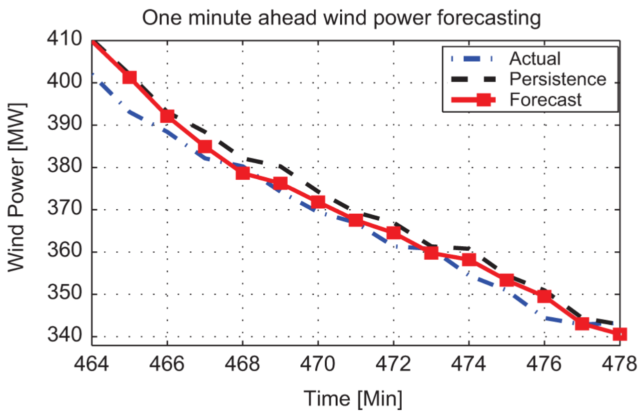

Fig. 3. Total wind power in ERCOT interconnection is forecasted through the GP. It was sampled on 7/7/2010. Wind power for 30 minutes is used to forecast the one minute ahead wind power. The normalized root mean square error (NRMSE) of the GP model is 0.0208, but the NRMSE of the persistence model is 0.0228.

In Fig. 3, wind data for 30 minutes prior to the forecasting time is used to forecast the one minute ahead wind power. The covariance matrix is fixed after it is trained, so it is off-line learning. We can observe that the persistence model has a phase shift error when the wind power decreases. On the contrary, the GP model recognizes that wind is decreasing, and it forecasts a lower production than the persistence model and predicts a ramp down in production. The persistence model, by construction, cannot predict the ramp. Nevertheless, the forecast error with the GP is only slightly better than with the persistence model.

IV. Stochastic Optimization for the Storage System

In this section, the mechanism of the storage system is described. Then, the stochastic optimization framework for the storage operation is formulated by building different constraints for different relationships between previous net production and newly generated wind power.

A. Mechanism of the Storage System

Under the assumption that the storage system is an electrochemical battery, important terminology and the mechanism of the storage system are enumerated. a) First, the storage size represents the maximum exchangeable energy which can be stored. b) Second, the power rating represents the maximum amount of exchangeable power output. The storage system can exchange output power within the power rating. c) Third, the state of charge (SOC) level represents the level of saved energy with respect to the storage size. In the electro-chemical battery, the SOC level is managed by the terminal voltage and current, but in our application, the SOC is managed directly by adding and subtracting power. Accordingly, the terminal voltage and current of the storage system was not considered explicitly. d) Finally, round-trip efficiency E represents the ratio of discharged energy to charged energy. When scheduled energy is discharged, it is divided by the square root of the round-trip efficiency and subtracted from the SOC level. In contrast, when energy is charged, it is multiplied by the square root of the round-trip efficiency and added to the SOC level. The efficiency is assumed as 90%, which is typical for an electro-chemical battery. Other technologies have different round trip efficiencies.

For every operation interval, the storage has one of three conditions: charging, discharging, or inactive. Some battery storage systems cannot fully charge because of the battery's internal resistance. Furthermore, the lifetime of a storage system is a function of the depth of the discharge, so the storage size is limited to tradeoff between the replacement period and power output. It is assumed that the storage can be charged only up to 90% of its size, and it can be discharged only down to 10% of its size. This is typical for an electro-chemical battery, but different SOC levels may be appropriate for other technologies. The convention used here is that the storage output is positive for discharging and negative for charging. The storage system is used to limit the ramp rate of the net production. Finally, we implement a new technique in our application. When the storage is depleted, because of the power rating difference between the net production and wind power, a severe ramp rate occurs. In order to avoid this catastrophe, the storage system reduces its power level even though this further violates RRLs. This method is called the soft landing technique.

B. Basic Stochastic Optimization Formulation

For the given net production at t, the wind power is measured at $t+1$. For the given wind power, the wind power at $t+2$ is forecasted with its PDF. Then, the storage operation at $t+1$ is chosen by solving a two-stage stochastic linear problem with a fixed recourse that minimizes the financial penalty incurred when violating RRLs. The first stage of the decision is the current amount of storage output, and the second stage of the decision is the future amount of storage output with respect to the forecasted wind power. In this optimization problem, it is assumed that there is a financial penalty for deviating outside the RRLs. It is also assumed that storage size and power rating are given, but we will calculate the economically optimal power rating and storage size in the next section.

The two-stage stochastic linear problem with fixed recourse is defined in [28] as:

$$\begin{array}{ll} \min\limits_{x,y} & c^T x + E_\omega \left[\min q(\omega)^T y(\omega)\right] \\ s.t. & Ax \qquad\qquad\quad = B \\ & T(\omega)x + Wy(\omega) = h(\omega) \\ & \qquad x \geq 0, y(\omega) \geq 0 \end{array} \tag{13}$$

where x is the first stage decision, and y is the second stage decision. Since W is fixed, (13) is called a fixed recourse problem. Suppose the random vector ω has K finite realizations with index $k = 1, \ldots, K$ and their probabilities of discrete distribution are given as p_k. Then, we can convert (13) into the deterministic extensive form as:

$$\begin{array}{ll} \min\limits_{x,y} & c^T x + \sum_{k=1}^{K} p_k q_k^T y_k \\ s.t. & Ax \qquad = B, \\ & T_k x + W y_k = h_k, \quad k = 1, \ldots, K \\ & \;x \geq 0, y_k \geq 0, \qquad k = 1, \ldots, K \end{array}. \tag{14}$$

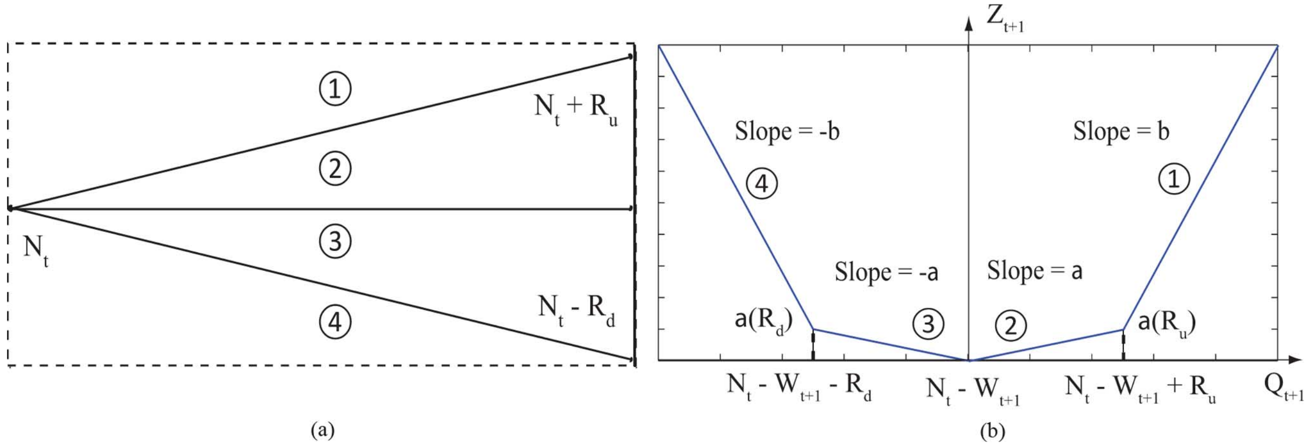

Fig. 4. (a) The areas of wind power with respect to the previous net production are plotted in the left figure. The area 1corresponds to ramp events violating ramp-up limit, the areas ② and ③ correspond to moderate ramp events, and the area 4 corresponds to ramp events violating ramp-down limit. (b) The penalty functions of those areas are also plotted in the right figure.

C. Designing Stochastic Optimization Problem

To represent the storage operation, vectors in the objective function, decision variables, and constraints in (14) are specified. Suppose wind power W_{t+1} would increase net production at time t by more than the ramp-up limit R_u:

$$N_t + R_u \leq W_{t+1}. \tag{15}$$

The relationship between the R_u and W_{t+1} is shown in Fig. 4(a). When wind power violates the R_u, in order to limit the ramp rate of the net production N_{t+1}, the objective function should decide the storage operation Q_{t+1} to minimize the financial penalty, which is linearly proportional to the number of MW above the RRLs. Therefore, the penalty function can be visualized using the graph in Fig. 4(b), where a is the slope of the penalty function within the RRLs, and where b is the slope of the penalty function outside of the RRLs. The penalty a is given within the RRLs to slightly encourage low ramp rates, and it is a very small number. It should be noted that the function in Fig. 4(b) is a piecewise linear convex penalty function, so it can be represented by a total penalty Z_{t+1} and the constraints:

$$Z_{t+1} \geq b(Q_{t+1} + W_{t+1} - N_t - R_u) + aR_u \tag{16}$$
$$Z_{t+1} \geq a(Q_{t+1} + W_{t+1} - N_t) \tag{17}$$
$$Z_{t+1} \geq -a(Q_{t+1} + W_{t+1} - N_t) \tag{18}$$
$$Z_{t+1} \geq -b(Q_{t+1} + W_{t+1} - N_t + R_d) + aR_d. \tag{19}$$

Equation (16) corresponds to the area ① in Fig. 4(a) and the slope ① in Fig. 4(b), (17) corresponds to the area ② in Fig. 4(a) and the slope ② in Fig. 4(b), (18) corresponds to the area ③ in Fig. 4(a) and the slope ③ in Fig. 4(b), and (19) corresponds to the area ④ in Fig. 4(a) and the slope ④ in Fig. 4(b). Since Z_{t+1} and Q_{t+1} should be chosen, and N_{t+1} is required for the second stage, the first stage of decision x should consist of:

$$x = [Z_{t+1}, Q_{t+1}, N_{t+1}]^T. \tag{20}$$

For the second stage objective, constraints are determined by the relationship between the net production N_{t+1}^k and forecasted wind power W_{t+2}^k, analogously to the first stage objective function. Therefore, y_k consists of:

$$y_k = \left[Z_{t+2}^k,\ Q_{t+2}^k,\ N_{t+2}^k\right]^T \tag{21}$$

where k represents the number of scenarios. Constraints for the second stage can be formulated in the same way that constraints for the first stage are calculated.

The vectors c and q_k in (14) are all equal to $[1, d, 0]^T$, where d represents the cost of the storage operation. The parameter d is used to limit excessive storage operations and represent the costs caused by the depth of discharge. It decides the relative value of storage operation compared to the penalty slopes of ramp rate violation a and b. There is another role of d. When the wind blows within the RRLs, the penalty function tries to control the storage operation to have a zero ramp rate. However, this phenomenon rarely happens since d is designed to impose the cost proportional to the amount of storage operations.

Finally, the objective function in our application is defined here:

$$\min\ Z_{t+1} + d\left|Q_{t+1}\right| + \sum_{k=1}^{K} p_k \times \left[Z_{t+2}^k + d\left|Q_{t+2}^k\right|\right]. \tag{22}$$

Four constraints in (16), (17), (18), and (19) are required. Furthermore, Q_{t+1} should be limited by the power rating PR:

$$-PR \leq Q_{t+1} \leq PR. \tag{23}$$

In addition, the absolute sign can be removed by a simple replacement:

$$Q_t = Q_t^D - Q_t^C \tag{24}$$

where $0 \leq Q_t^D, Q_t^C \leq PR$. The equality constraint is obtained as:

$$N_{t'} = W_{t'} + Q_{t'} \tag{25}$$

where t' is $t+1$ and $t+2$. Furthermore, the SOC level should be managed to be within the maximum and minimum SOC levels. Therefore,

$$\text{Sto} \times l \leq SOC_{t+1} \leq \text{Sto} \times u \tag{26}$$

where SOC_{t+1} is defined as

$$SOC_{t+1} = SOC_t - \frac{T_{\text{int}}}{60} \times (\max(Q_{t+1}, 0) \times \frac{1}{\sqrt{E}} + \min(Q_{t+1}, 0) \times \sqrt{E}). \tag{27}$$

The $\max$ and $\min$ functions are replaced by using (24).

As the number of scenarios K increases, the number of decision variables in (14) and constraints also increase. A single wind scenario adds four constraints for penalty costs, two constraints for the SOC management, two constraints for power rating control, and one equality constraint for net production. In order to reduce the number of constraints, the decomposition theorem, known as Benders Decomposition, was proposed in [29]. It was developed in [30] to solve two-stage recourse problems for the continuous distribution cases by utilizing the L-shaped constraints in (14), so it is also known as the L-shaped method.

D. Simulation Results

Simulation conditions are as follows. Wind power was sampled on July 2010, and its total capacity is 8930 MW. Wind power outputs for 30 steps are used to forecast the one step-ahead wind power. The operation interval is one minute, and the number of scenarios is 100. Both the upper and lower RRLs are 10 MW/min. The storage size is 1200 MWh, and the power rating is 200 MW. Furthermore, the round trip efficiency is 0.9, and the initial SOC level is 0.5. In the simulation of monthly wind power, the stochastic operation pays \$248.8712 million in penalties, but the deterministic operation pays \$249.314 million in penalties. Therefore, we can say that the stochastic operation can reduce the penalties.

Fig. 5 shows that the stochastic storage system limits the ramp rates of net production. The stochastic storage system is compared to that of an unlimited storage system. At minutes 150 and 200, the limited storage cannot limit the ramp-up rate because of its limited power rating. The soft landing technique is used between minute 200 and 250 to delay the storage collapse, but the storage system does not work any more after minute 250 because of insufficient SOC levels. This contrasts to the net production of an unlimited storage system. At around minute 600, both operations have different paths because the starting points of the unlimited and stochastic operations are different. It should be noted that at minute 950, the stochastic storage operation charges more than the minimum to avoid violating the ramp rate since it prepares for ramp-down events where charged energy will be discharged.

The simulation in Fig. 6 shows that the stochastic operation outperforms the deterministic operation. The path is designed to emphasize the performance of our algorithms. It is assumed that there is a large ramp-up event between minute two and three. First, consider stochastic operation. After forecasting the ramp-up event, the storage discharges at minute two in order to reduce the ramp rate, so the total financial cost is reduced. By discharging more energy, the storage system can prepare for a future larger ramp-up event by leaving space to charge. Furthermore, at minute four, even though wind power is reduced, the stochastic storage system discharges slightly more in order to prepare for the next ramp-up event. In contrast, the net production of the deterministic operation follows the wind power and causes a larger ramp-up rate subsequently, when its capacity is reached.

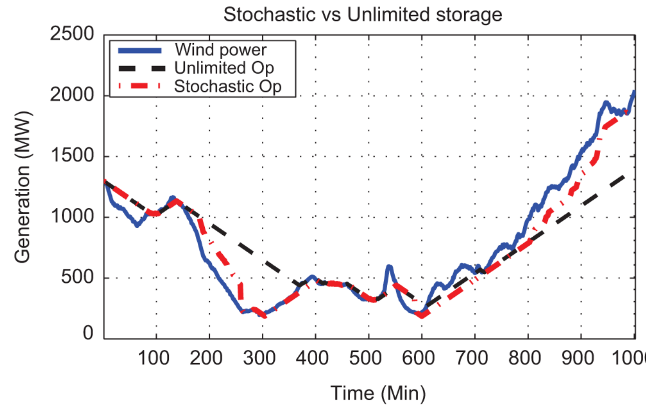

Fig. 5. The stochastic storage operation is compared to the storage operation with an unlimited storage system. It shows that the stochastic storage operation well limits the ramp rates required by the unlimited storage.

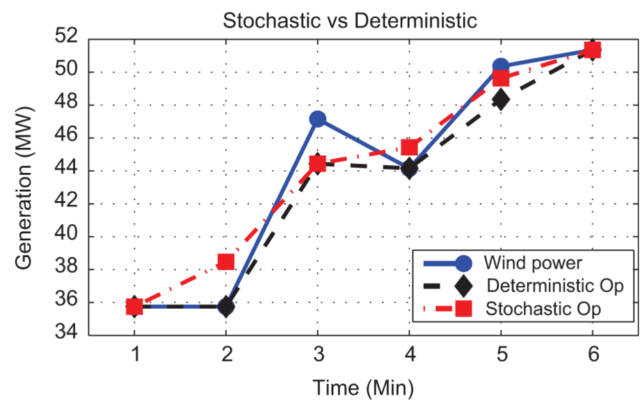

Fig. 6. The path of wind power output is simulated. The stochastic storage operation is compared to the deterministic storage operation with the same power rating and power efficiency. In continuous ramp-up events, the stochastic system discharges more in preparation for future charging.

V. Economic Storage Sizing

In this section, an economic storage specification to limit the ramp rates of net production is chosen by running the stochastic storage operation recursively.

A. Optimization for the Storage Sizing

The process of deciding the economic storage size is enumerated here. Suppose that the RRL is given. i) First, we calculate the total cost to have an ideal net production curve satisfying all RRLs. This is the opportunity cost to keep wind power within the RRL. It includes the costs of regulation up services, costs of energy, costs of curtailed wind power, and costs of CO_2 emissions. We assume this cost is passed on to the consumers in the form of higher electricity prices. The penalty is given not only to operate the storage system in a stochastic way but also to provide adequate penalties to the ISO operators so that they respond to limiting ramp rates. ii) Based on that opportunity cost, the penalty $\$24/\mathrm{MW}$ per period is decided so that the total penalty should be same as the total opportunity cost. iii) As the storage size increases from a minimum to a maximum size, the storage operation is run to calculate the penalty cost, which becomes a function of the storage size. Since the given storage size is not large enough to satisfy all constraints, the penalty cost should be paid. iv) At the same time, the annual storage cost is decided based on the storage size. The optimal storage size is decided when the sum of storage costs and penalty costs is minimized. We assume that a grid-level storage system is centrally installed, so the distributed storage applications are not considered. If a storage system is installed by an individual wind farm owner, the smoothing effect of geographically distributed wind farms is not utilized, so the total storage size needed will increase. Therefore, we simulated total wind power in ERCOT interconnection.

B. Cost Function of the Storage System

The process to calculate the storage cost is described based on [31]. For the given storage size Sto and power rating PR, annual storage cost (ASC) consists of the annual financing costs (AFC), annual replacement costs (ARC), annual fixed and variable maintenance costs (AMC), and annual operation costs (AOC):

$$\mathrm{ASC} = \mathrm{CRF} \times [\mathrm{AFC} + \mathrm{ARC} + \mathrm{AMC} + \mathrm{AOC}] \tag{28}$$

where the ASC could be the break even cost for the storage application. The capital recovery factor (CRF) for the given interest rate r and service life n is defined in

$$\mathrm{CRF} = \frac{r(1+r)^n}{(1+r)^n - 1}. \tag{29}$$

In detail, the AFC includes installation costs, interest, taxes, and insurance, but we only consider installation costs. Installation costs include storage size cost (SSC) per MWh, power rating cost per MW, and balance of plant (BOP) per MWh. The SSC includes the commercial space to increase storage size. The power rating cost is the power electronic cost (PEC) to increase output power. In addition, the BOP includes the substation, transformer, land lease, building, and labor costs. Therefore, the AFC is defined as:

$$\mathrm{AFC} = \mathrm{SSC} \times Sto + \mathrm{PEC} \times PR + \mathrm{BOP} \times Sto. \tag{30}$$

Second, the ARC can be calculated as

$$\mathrm{ARC} = \mathrm{FRC} \times \frac{1}{(1+r)^R} \times \frac{Sto}{E} \tag{31}$$

where R is the replacement year, where the FRC is the future replacement cost, and where E is the round-trip efficiency. Third, since only the fixed maintenance is considered, the AMC can be calculated as

$$\mathrm{AMC} = \mathrm{MC} \times PR \tag{32}$$

where the MC is the annual maintenance cost per the power rating. Finally, the AOC is added. In summary, the ASC can be represented as the function of the storage size as:

$$\begin{aligned}\mathrm{ASC}(Sto) = {}& Sto \times \left[\frac{\mathrm{SSC} + \mathrm{PEC}}{\mathrm{MDD}} + \mathrm{BOP}\right] \\ & + Sto \times \left[\frac{\mathrm{FRC}}{E(1+r)^R}\right] \\ & + Sto \times \left[\frac{\mathrm{MC}}{\mathrm{MDD}}\right] + \mathrm{AOC}\end{aligned} \tag{33}$$

where the MDD is the maximum discharging duration, which is set at six hours in our application. It is worth noting that benefits from other storage operations, such as capacity firming, energy arbitrage, or voltage support are not considered. Furthermore, even though value of deferring additional transmission lines and substation components is important, it is not considered here. The additional cost for the power electronics to boost battery voltage is excluded as well.

C. Cost & Benefit Analysis of the Storage System

The optimal storage specification is estimated. To keep the $10\ \mathrm{MW/min}$ RRLs through conventional generators, $\$243.39$ million is required. The average energy price, amounts of wind power curtailment, and costs of $\mathrm{CO_2}$ emissions are considered in this calculation. For the AS costs, the average regulation up price and cost of provided energy are used since ramp-up events can be limited via curtailment. If an unlimited storage system is used to keep these RRLs, 2017 MW power rating and 7564 MWh storage size are required. However, purchasing this storage specification costs $\$2413.8$ million, which is much higher than the costs through conventional generators. The total energy profit in July is $\$2450.1$ million, of which the storage cost is 27%. In order to keep within the RRLs, we set the penalty cost as $\$2420.4971/\mathrm{MW}$. Costs of a NaS (Sodium-Sulfur) battery is used to analyze the costs. In the storage cost calculation, the number of cycles, utilization factor, and depth of discharge are ignored, so the ARC becomes zero. Furthermore, the service life is set at 10 years, and the MC is set as 3% of capital cost. Other parameters for the cost analysis are referred from [32].

Fig. 7 shows the curves for the storage costs, penalty costs, and total costs. It is clearly observed that the monthly storage costs increase as the storage size increases. We can also observe that the penalty costs decrease as the storage size increases, since many ramp events that would have violated the RRLs are avoided by the storage operation. The penalty cost curve follows the exponential curve approximately, which means that most ramps are below a certain size, and extremely large ramp events are rare. This corresponds to the fact that a very large storage specification is required to limit all ramp events. Furthermore, Fig. 2 also supports the fact that a small size storage system can reduce the amounts of AS significantly because the variability curve approximately follows the square root of wind power capacity. In Fig. 7, when the total cost reaches its lowest value, the optimal storage size is estimated as 280 MWh, and the optimal power rating is set as 46.667 MW. The total cost is $\$241.51$ million, or 3% of monthly total profit.

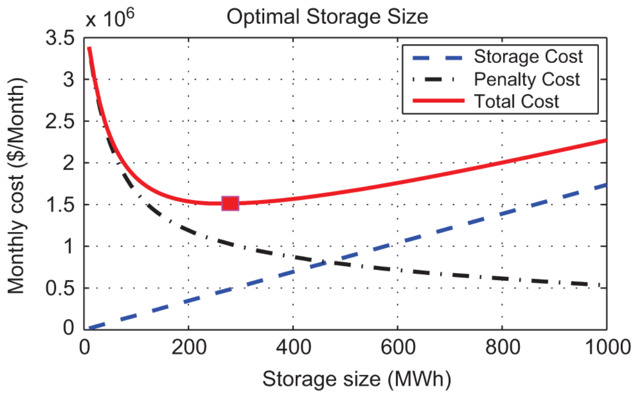

Fig. 7. Total wind power capacity is 8930 MW. The RRL was 10 MW/Min. The optimal ramp rate is 46.67 MW, and the optimal storage size is 280 MWh. The total cost to limit ramp rate is $1.51 million per month.

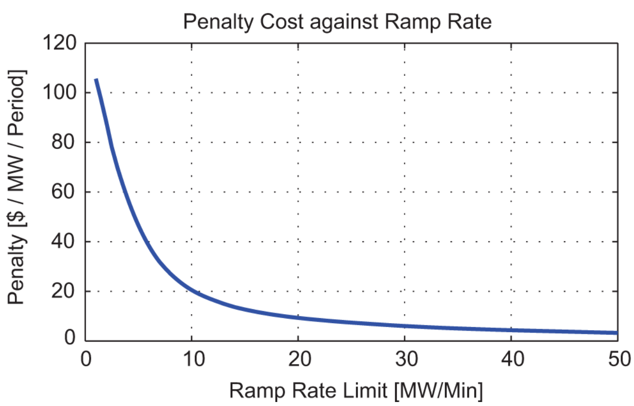

Fig. 8. The penalty cost is plotted as the RRL increases. As the RRL is relaxed, the penalty cost decreases by approximately following an exponential curve.

In addition, Fig. 8 shows that the penalty cost per MW decreases as the RRL increases. As mentioned above, the total penalty costs are the same as the total costs to keep all the RRLs through conventional generators. The penalty cost follows the power curve approximately, so it decreases fast when the RRL is below 10 MW/Min. As a result, to apply more strict RRLs, higher penalty costs should be charged. This result also shows that most ramp rates are confined within a certain range, and large ramp events rarely occur. In some situations, the penalty cost should be set very high. However, since it is difficult to reflect those events in our simulation, we assume that the penalty cost is a fixed base cost. Even though it is fixed, since it is close to the regulation up cost, it might give enough incentive to wind farm owners or ISO operators to invest money in the central storage system.

VI. Conclusion

A stochastic optimization framework for the storage operation is established to limit the ramp rate of the net production. The penalty for violating the RRL is set per $\$24/\mathrm{MW}$ per period so that total penalty costs without a storage system cover total costs to keep all ramp rates within the RRLs through conventional generators. To reduce the total penalty costs, the storage operation is chosen by solving a two-stage stochastic linear program with fixed recourse based on the forecasted wind power. The economic storage specification is chosen by running the storage operation recursively with different storage

TABLE I
Cost Parameters of the Storage System [32]

Parameters	Name	Value
Electricity Price	Energy Price	50 $ / MWh
	Regulation Up Price	30 $ / MW
	CO_2 Emission Price	25 $ / MWh
Financial Cost	Installation Cost	150 $ / kWh
	Interest Rate	7 %
	Service Life	10 years
Storage Cost	Balance of Plant	50 $ / kWh
	Power Electronics Cost	125 $ / kW
	Replacement Cost	0 $ / kWh
	Maintenance Cost	5 $ / kWh
	Operation Cost	5 $ / kWh

specifications. The most important results of this work are: i) The stochastic storage operation with forecasted wind power performs better than the deterministic operation without the forecasted information in managing the SOC level. ii) The GP outperforms the persistence model in forecasting short-term wind power, and it provides the conditional distribution of future wind power to the stochastic optimization framework. iii) Since most ramp rates are within a certain size, the storage system with a small specification can reduce the total penalty costs including costs of AS significantly although it cannot limit all ramp rates. Considering these results, we come to the following conclusion. Even though a storage system is too expensive to fully provide all ancillary services, it might be valuable to invest in a small storage system with advanced storage operation techniques, such as a stochastic optimization, the soft landing technique, and wind power forecasting. Furthermore, the storage system will become more attractive if penalty costs are properly set to reduce total costs to mitigate wind power variability. This conclusion requires two assumptions: wind farms are geographically distributed, and the storage system is centrally installed and controlled. Furthermore, although the storage system in our application is assumed to be an electro-chemical battery, the optimization formulation may be applied to any form of storage device, such as a compressed air storage, electric vehicles, and pumped hydroelectric power.

Future work includes investigating the power difference for an operation interval and representing forecasting errors using the Laplace distribution [33]. Therefore, a GP with a different likelihood function and prior, such as the Laplace distribution, can be used to describe the wind power. Furthermore, even though one step ahead wind power is forecasted in our application, wind power outputs in multiple steps can be forecasted through the NWP.

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