Optimal Storage-Aided Wind Generation Integration Considering Ramping Requirements

Lin Xiang, Derrick Wing Kwan Ng, Woongsup Lee, and Robert Schober
Institute for Digital Communications, Universität Erlangen-Nürnberg, D-91058 Erlangen, Germany
Email: {linxiang,kwan,lee,schober}@lnt.de

Abstract— **Large-scale integration of intermittent wind energy can put a large burden on the utility company in balancing system demand and supply. As more and more dispersed wind energy suppliers connect to the system for electricity supply, the power system suffers from increased operation cost and risk caused by the discrepant interests of energy suppliers and the utility company. Energy suppliers may only concern about maximizing their own profits by pushing as much energy into the grid as possible, while neglecting the risk of steep ramps in wind generation. In this paper, exploiting the two-way communication capability in smart grid, we propose interactive ramp control of wind energy integration by aligning the individual pursuits of the energy suppliers and the utility company for social welfare maximization. The optimal wind energy integration and generator ramp control are investigated in an offline social welfare optimization problem assuming full knowledge of future wind energy and load demand. Moreover, the benefits of storage are exploited in our proposed storage-aided generation range adaption scheme to reduce the potential risk caused by inaccurate wind energy forecasts and the ramping latency of slow generators. Furthermore, a suboptimal storage-aided generation range adaption scheme with low computational complexity is presented for online control of wind integration when wind energy forecasts are unavailable. Our simulation results show that interactive ramp control is necessary to achieve efficient and secure wind energy integration and with the aid of storage, the power system's ramping capability can be improved at lower operation cost.**

Index Terms— **Smart grid, large-scale integration, ramp control**

I. Introduction

Wind energy is considered as eco-friendly, sustainable, and increasingly important energy source for the future power system. However, due to its inherent temporal variations, the presence of wind energy can cause an operational burden in frequency regulation and stabilization for balancing power generation and load [1]. Besides, wind generation is not fully predictable. For large-scale integration, the steep ramps in wind energy [2] increase the power system's risk of supply shortage and over-generation [3]. Thus, the effective integration of volatile wind energy into the power grid with manageable supply uncertainty and guaranteed system reliability becomes a crucial issue.

Wind generation is traditionally dispatched as "negative load" in the unit commitment process [4] due to the limited controllability of wind energy compared to conventional energy sources like coal and gas. For large-scale integration, the utility company (UC) needs to provide enough operating reserves of online or offline generation capacity of conventional generators to deal with the large ramps in wind generation. The optimal reserve requirement that achieves minimum operation cost was investigated in [3] using a two-stage stochastic unit commitment model. However, scheduling wind energy as an inelastic ("must-take") negative load can lead to costly system operation for large-scale wind generation integration because of the high reliance on expensive fast operating reserves [5].

Active scheduling through wind generation curtailment and ramp rate control[1] has been recently proposed to promote large-scale wind energy integration at balanced operation costs [6]–[9]. In [6], the variations of the residual load, i.e., the part of the load that is not served by wind energy, are shown to be accelerated due to large ramps of wind energy for large-scale integration. Besides, the authors demonstrate that by curtailing wind generation ramps, e.g., through controlling the pitch angle of a wind turbine, the ramps in the residual load can be managed with less costly slow generators, thus lowering average operation cost [6]. Furthermore, wind generation curtailment can relax the transmission line constraints in the distribution system and increase the effective wind energy usage within acceptable voltage/current variation levels [7]. On the other hand, the use of storage in ramp control decouples the generation and consumption of wind energy and can lead to an improvement in both operation cost and wind energy usage [8], [9]. However, wind energy curtailment and ramp control need to be planned based on accurate forecasts of wind generation and load demand over a large time period; otherwise, the limited ramping capability of slow generators may result in ramping violations. Sensitivity to both forecast errors and accumulated forecast errors hampers the realtime implementation of wind energy curtailment schemes. Moreover, the charging and discharging operations can reduce the storage lifetime with current storage techniques [10]. This effect can not be simply neglected in exploring the role of storage to promote large-scale wind energy integration.

The above research [3]–[9] has focused on centralized control of wind energy integration from the UC's perspective. As the grid interface for wind integration becomes standardized with the application of power electronics [11], it is expected that more and more dispersed wind generators, including private wind farms and home-use wind turbines, will connect to the power system for electricity supply. This trend requires an intelligent ramp control for the *aggregate* wind generations. However, coordinating the renewable energy suppliers (RESs) with the UC poses a challenge for achieving efficient wind energy integration and secure power system operation. Since the operational burdens and costs incurred by wind energy ramps (e.g., in generator ramp control) are usually unseen at the RES's side, RESs may try to integrate as much renewable energy as possible for their own profit maximization, which can deteriorate power system security in case of "over-generation".

Exploiting the two-way communication capability of smart grid, interactive ramp control of the integration process is possible based on realtime information exchange between the UC and the RESs. In this context, this paper investigates the optimal interactive ramp control for large-scale integration of dispersed wind generation to align the behaviors of the RESs and the UC in wind energy

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[1]The term "wind curtailment" stresses the reduction of the wind generation level, while "ramp control" emphasizes on restricting the rate of change of generation levels. In this paper, since we focus on a time slotted system, the two terms are used interchangeably.

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integration and generator ramp control. By modeling the preferences and behaviors of both UC and RESs, the social welfare, i.e., the net system benefit minus the system operation cost (including storage operation cost accounting for the impact of charging and discharging on the storage lifetime), is proposed as system control objective. The optimal wind energy integration considering the generator's ramping requirements are obtained based on an offline optimization problem assuming full knowledge of wind energy arrivals and load demands. Furthermore, in addressing the sensitivity problem caused by forecast errors, we propose a storage-aided generation range adaption scheme to extend the ramping capability of slow generators by properly utilizing the storage units. A suboptimal online storage-aided ramp control scheme is implemented assuming no knowledge of future wind generations. Simulation results show the benefits of interactive ramp control in achieving efficient and reliable wind energy integration, and with the aid of storage, the system's ramping capability can be strengthened at low operation cost.

The rest of this paper is organized as follows: Section II presents the system model in detail. In Section III, the social welfare optimization problem is investigated, and a suboptimal online scheme for storage-aided generation range adaption is proposed. Section IV presents simulation results for the proposed schemes and finally, Section V concludes the paper.

II. System Model

A. Deregulated Power System and Wind Integration Control

For a deregulated electricity system, assume N RESs, denoted by $\mathcal{N}$, $|\mathcal{N}| = N$ ($|\cdot|$ denotes the cardinality of a set), connect to the power system to provide electricity generated by their own wind farms. The UC of the power system operates conventional generators to accommodate the time-varying wind energy supply and to maintain the system's operational security. The RESs and the UC are connected via a two-way communication network. The activities of the RESs and the UC are synchronized. Fig. 1 depicts the system model.

The system's operation cycle is divided into K time slots, each of which has a duration of Δt. The wind generation and system load are assumed to be constant over one time slot[2]. In our proposed interactive ramp control, the UC and the RESs collaborate in wind integration and generator ramp control through information exchange over the communication network. The UC allocates the serving load, which is assumed inelastic ("must-take"), to the RESs in the generation ramp control process at the beginning of each time slot. In response, the RESs serve the allocated load by managing the energy flows in wind generation and storage charging/discharging. Let d_k be the total load at time k. The amount of serving load allocated to RES i at time k is denoted by $d_k^{(i)}, \forall i \in \mathcal{N}$, and the total allocation does not exceed the total demand load,

$$d_k \geq \sum_{i=1}^{N} d_k^{(i)}, \ \forall k. \tag{1}$$

To maintain the total supply and demand balanced, the residual load, $(d_k - \sum_{i=1}^{N} d_k^{(i)})$, is served by the UC using conventional generators.

The need for interactive ramp control lies in two aspects. First, the amount of wind energy integration of RESs depends on the ramping capability of the conventional generators in the power system. This is because the time-varying wind energy supply will

[2]The time scale defined above is used for the fine control (in seconds or minutes) of instantaneously varying wind generations. In practice, a large time scale (e.g. an hour) can be used for the coarser ramp control of average wind generations [12].

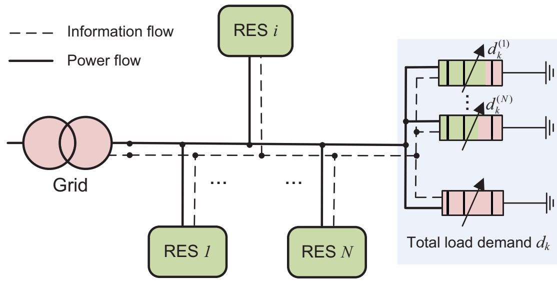

Fig. 1. Power system model.

"accelerate" the fluctuations in the residual load [6], which has to be accommodated by the UC. On the other hand, the load allocation and the generator ramp control at the UC are based not only on the system load and the conventional generators' ramping status, but also on the feedback information from the RES regarding the amount of wind generation and the stored energy. The details of RES energy management and UC generation ramp control will be explained in Sections II-B and II-C, respectively.

Considering the UC as a *virtual* "consumer" of wind energy, the end customer's role is not considered in this paper. During the energy exchange, the UC gains environmental and/or economical benefits from "consuming" (integrating) wind energy; while the RESs gain monetary revenue from the UC for wind energy supply. The revenue of RESs is either determined by the energy price and the amount of integrated energy at each time slot or specified in a predefined contract[3]. Based on microeconomic theory, the UC's corresponding level of satisfaction is modeled as a sum of utility values gained from each RES's renewable energy supply, $\sum_{i=1}^{N} U_d(d_k^{(i)}, \delta_d)$, where $U_d(\cdot)$ models the UC's utility value regarding one RES's wind integration and δ_d reflects the UC's preference for wind energy integration. The value of δ_d depends on the installed wind generation capacity, the generation variation statistics of the RESs, and the government's subsidy policy on wind integration.

Utility function $U_d(d_k^{(i)}, \delta_d)$ is assumed to satisfy the following properties [13]:

(i) The utility function is nondecreasing and concave, i.e., the marginal benefit is nonincreasing, with respect to the wind energy supply $d_k^{(i)}$;
(ii) The utility function increases with preference δ_d of integrating wind energy;
(iii) The utility function value is nonnegative and equals zero when there is no supply.

An example of a utility function that fulfills the above properties is the quadratic utility function, which has been largely used in recent practice in energy consumption modeling [13],

$$U_d(x, \delta_d) = \begin{cases} \delta_d x - \frac{\alpha_d}{2} x^2 & \text{if } 0 \leq x < \frac{\delta_d}{\alpha_d} \\ \frac{\delta_d^2}{2\alpha_d} & \text{if } x \geq \frac{\delta_d}{\alpha_d} \end{cases}, \tag{2}$$

where α_d is a pre-determined parameter.

B. RES Energy Management

The energy management at the RESs focuses on serving the allocated load with intermittent wind generation, as shown in Fig. 2. Let the wind energy arrival of RES i at time k be $e_k^{(i)}$. The actual amount of wind generation at time k, denoted as $p_k^{(i)}$, depends on the ramp control decisions of the system. The adjustment of wind generation can be done by controlling the pitch angles of wind turbines. In this paper, we assume the conversion

[3]The revenue of RESs is not modeled in this paper, since it cancels with the UC's payment in the social welfare objective.

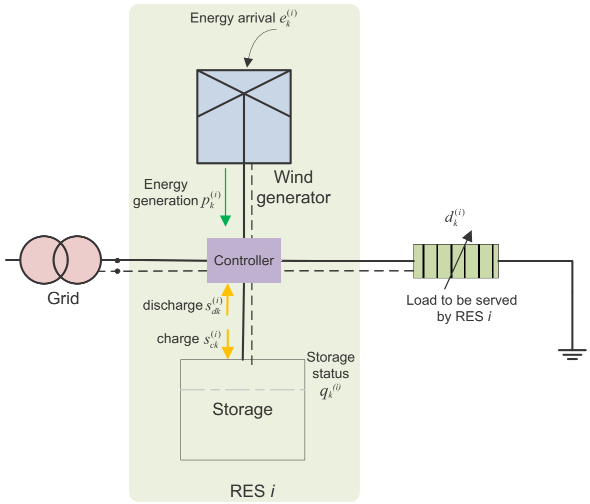

Fig. 2. Block diagram of RES energy management system.

loss during the wind generation process is negligible, which leads to

$$0 \le p_k^{(i)} \le e_k^{(i)},\ \forall i, k. \tag{3}$$

Besides, a portion of the RESs, denoted by $\mathcal{N}_s \subseteq \mathcal{N}$, $|\mathcal{N}_s| = N_s \le N$, are equipped with energy storage units to store excess wind generation for backup use during low generation periods[4]. At time k, a RES with storage can decide to charge (discharge) the storage units with an amount of $s_{c,k}^{(i)}$ ($s_{d,k}^{(i)}$) of energy. The storage status, denoted as $q_k^{(i)}$, evolves as

$$q_k^{(i)} = q_{k-1}^{(i)} + \eta_c s_{c,k}^{(i)} - s_{d,k}^{(i)}/\eta_d,\ \forall i, k \tag{4}$$

where $q_0^{(i)}$ is the initial storage status for RES i; η_c and η_d denote the charging and the discharging efficiencies, respectively, and $\eta_c, \eta_d \in (0, 1]$. The maximal energy capacity of the storage unit is denoted as $B_{\max}$, and a minimum amount of $B_{\min}$ of energy needs to be held in the storage unit. Then, we have

$$B_{\min} \le q_k^{(i)} \le B_{\max}, \forall i \in \mathcal{N}_s, \forall k. \tag{5}$$

Considering the maximal charging and discharging powers, denoted as Q_c and Q_d, respectively, we get

$$0 \le s_{d,k}^{(i)} \le Q_d \Delta t;\ 0 \le s_{c,k}^{(i)} \le Q_c \Delta t,\ \forall i \in \mathcal{N}_s, \forall k. \tag{6}$$

Note that, if storage is unavailable, then we set $q_k^{(i)} = s_{c,k}^{(i)} = s_{d,k}^{(i)} = 0, \forall i \notin \mathcal{N}_s, \forall k$.

In each time slot, the RESs supply wind energy from their generated and stored energy. The amount of supplied energy is equal to the assigned load, i.e.,

$$p_k^{(i)} - s_{c,k}^{(i)} + s_{d,k}^{(i)} = d_k^{(i)},\ \forall i, k. \tag{7}$$

The decision vector of RES i at time k is denoted as $\mathbf{x}_k^{(i)} = [p_k^{(i)}, s_{c,k}^{(i)}, s_{d,k}^{(i)}]$. Instead of manual decisions, a central controller is responsible for information collection and decision making, on behalf of the RESs.

The charging and discharging process can reduce the lifetime of energy storage and this effect should be taken into account in the storage operation cost [10]. Assuming linear charging and discharging "prices" $\rho_c s_{c,k}^{(i)}$ and $\rho_d s_{d,k}^{(i)}$, i.e., the marginal storage operation costs are proportional to the amount of charged and discharged energy, respectively, the storage operation cost is modeled as [10]

$$C_{ek}^{(i)}\left(s_{c,k}^{(i)}, s_{d,k}^{(i)}\right) = \frac{\rho_c}{2}\left(s_{c,k}^{(i)}\right)^2 + \frac{\rho_d}{2}\left(s_{d,k}^{(i)}\right)^2 \tag{8}$$

where ρ_c and ρ_d are constants.

C. UC Generation Ramp Control

The generator ramp control is responsible for the RESs' load allocation and the residual load accommodation so that the ramping requirements of the conventional generators are satisfied. The conventional generators can be categorized as slow and fast generators with different ramping capability. Slow generators such as basic load generators and load following generators [15] have lower ramping rates, but can provide large amounts of cheap electricity. Usually, slow generators are scheduled to serve the basic load and less flexible load in the system. By contrast, fast generators, including peaking generators and spinning/non-spinning generators [3], have higher ramping rates and can respond within seconds at the expense of a higher cost due to the use of expensive fuels (e.g., gas). Fast generators are mainly used as operating reserves to deal with fluctuations in renewable supply and peak load.

Both fast and slow generators can contribute to accommodating the residual load. To this end, the residual load is decomposed into a slow-varying component, $d_{s,k}$, and a fast-varying component, $d_{f,k}$,

$$d_k - \sum_{i=1}^{N} d_k^{(i)} = d_{s,k} + d_{f,k},\ \forall k, \tag{9}$$

where $d_{s,k}$ and $d_{f,k}$ are accommodated by slow and fast generators, respectively. The values of $d_{s,k}$ and $d_{f,k}$ are determined by the generator ramping capability [3],

$$-R_s^{\max}\Delta t \le d_{s,k} - d_{s,k-1} \le R_s^{\max}\Delta t,\ \forall k, \tag{10}$$

$$-R_f^{\max}\Delta t \le d_{f,k} - d_{f,k-1} \le R_f^{\max}\Delta t,\ \forall k, \tag{11}$$

where $R_s^{\max}$ and $R_f^{\max}$ are the maximal ramping rates for slow and fast generators, respectively, and $R_f^{\max} \gg R_s^{\max}$.

Due to the lower ramping rate and expensive startup cost, the slow generator output is limited to a certain generation range [15],

$$G_s^{\min}\Delta t \le d_{s,k} \le G_s^{\max}\Delta t,\ \forall k, \tag{12}$$

where $G_s^{\min}$ and $G_s^{\max}$ are the corresponding minimum and maximal generation powers of the slow generators. In contrast, the fast generators' output is mainly constrained by the generation capacity $G_f^{\max}$. Thus, we have

$$0 \le d_{f,k} \le G_f^{\max}\Delta t,\ \forall k. \tag{13}$$

The control vector at the UC is denoted as $\mathbf{y}_k = [d_{s,k}, d_{f,k}, \{d_k^{(i)}\}_{i=1}^N]$. The generator ramp control incurs a total cost equal to the sum of the generation costs of the slow and fast generators, denoted by $C_s(\cdot)$ and $C_f(\cdot)$, respectively. Since each type of generator is actually a mix of generators with different capacities and costs, the empirical generation costs for slow and fast generators are piecewise linear and can be approximated by a quadratic function [14]:

$$C_m(L_k) = \frac{a_m}{2}L_k^2 + b_m L_k + c_m,\ m \in \{s, f\}, \tag{14}$$

where L_k denotes the generation level of the slow/fast generators; the fixed parameters a_m, b_m, and c_m satisfy $a_m > 0, b_m \ge 0$, $c_m \ge 0$, and $a_f L_k + b_f > a_s L_k + b_s, \forall L_k > 0$, implying that for the same amount of energy generation, the marginal cost of fast generators is larger than that of slow generators.

[4]In this paper, each RES is assumed to be a pure energy supplier and charging the storage units with grid power is not allowed.

III. Optimal Wind Energy Supply with Ramp Control

A. Social Welfare Optimization with Full Generation Range

The ramps in wind energy can result in higher costs for conventional generator ramp control. However, the RESs are fully unaware of such burden. Without ramp control, the RESs might simply inject as much wind energy into the grid as possible to increase their profits, which can deteriorate the system security in case of reserve shortage. To align the activities of all participants in the ramp control of wind energy integration, the social welfare, i.e., the net benefit of both the RESs and the UC minus the various system costs [13], is considered as the system control objective. Considering a finite time horizon of M time slots, the social welfare function is defined as the sum of the energy integration utility functions minus the total cost incurred in ramp control and storage operation during the whole time period:

$$W(\mathbf{x}, \mathbf{y}) = \sum_{k=1}^{M} W_k(\mathbf{x}_k, \mathbf{y}_k), \tag{15}$$

with

$$\begin{aligned} W_k(\mathbf{x}_k, \mathbf{y}_k) = \sum_{i=1}^{N} &\left[U_d\left(d_k^{(i)}, \delta_d\right) - C_{ek}^{(i)}\left(s_{c,k}^{(i)}, s_{d,k}^{(i)}\right)\right] \\ &- C_s(d_{s,k}) - C_f(d_{f,k}), \end{aligned} \tag{16}$$

where $\mathbf{x} = [\mathbf{x}_1, \cdots, \mathbf{x}_M]$, $\mathbf{x}_k = [\mathbf{x}_k^{(1)}, \cdots, \mathbf{x}_k^{(N)}]$, and $\mathbf{y} = [\mathbf{y}_1, \cdots, \mathbf{y}_M]$.

The optimal ramp control needs to be planned over a long time horizon and requires full knowledge of the future wind energy arrivals and load demand. Here, the offline social welfare optimization problem is solved first by assuming that wind energy and load demand are fully predictable. In a realtime system, the online control relies on dealing with the uncertainty inherent in wind energy and load demand. The offline optimum provides an upper bound for the performance of online schemes.

Assuming the wind energy and load demand are fully known or can be accurately forecast over the horizon of M time slots, the slow generators can be allowed to ramp in the full generation range, i.e., $d_{s,k} \in [G_s^{\min}\Delta t, G_f^{\max}\Delta t]$. The social welfare optimization problem with full generation range is formulated as,

$$\begin{aligned} &\underset{\mathbf{x},\mathbf{y}}{\text{Maximize}} && W(\mathbf{x}, \mathbf{y}) \\ &\text{Subject to} && (1), (3)-(7), (9)-(13). \end{aligned} \tag{17}$$

Problem (17) is a concave maximization problem [17] and can be solved by standard numerical solvers such as CVX [18]. Although an analytical solution is unavailable, the following observation can be made.

Proposition 1: The optimal charging and discharging decisions, $s_{c,k}^{(i)*}$ and $s_{d,k}^{(i)*}$, are complementary in each time slot, i.e., $s_{c,k}^{(i)*} \cdot s_{d,k}^{(i)*} = 0$, if the storage has i) infinite capacity, $B_{\max} \to \infty$, or ii) full charge/discharge efficiency, $\eta_c = \eta_d = 100\%$.

According to Proposition 1, an ideal storage is either charged or discharged in each time slot. We provide a sketch of the proof for i) by contradiction in [19]. The proof of ii) is similar.

B. Storage-Aided Generation Range Adaption and Online Implementation

The online implementation of the social welfare optimization scheme is hampered by: i) the ramping capability limitations of slow generators and ii) the reliance on (accurate) information about future wind energy arrivals and load demand. If the forecasts of wind energy and load demand are inaccurate or unavailable, full range generation ramping can put the system under risk of either insufficient energy supply or excess energy supply, due to the slow generator's latency in ramping up and down in consecutive time slots. Here, generation range adaption and the role of storage are explored to guarantee the requirements of system security when forecasts of wind energy and load demand are inaccurate or unavailable.

1) Storage-Aided Generation Range Adaption: A direct method to avoid the ramping latency of slow generators is to restrict the output variations of the slow generators to their ramping range, i.e.,

$$g_{\min}\Delta t \leq d_{s,k} \leq g_{\max}\Delta t, \tag{18}$$

where $g_{\min}$ and $g_{\max}$ are the allowable generation power limits. The values of $g_{\min}$ and $g_{\max}$ satisfy

$$0 \leq g_{\max} - g_{\min} \leq R_s^{\max}, \tag{19}$$

$$g_{\min} \geq G_s^{\min}, g_{\max} \leq G_s^{\max}. \tag{20}$$

On the other hand, (18) can result in inefficient ramp control when the slow generators have enough ramping capability but can not ramp to the desired generation power due to (18). To overcome this problem, the role of storage is exploited to extend the effective output range of the slow generators, instead of only using storage for wind energy backup in the previous schemes. The idea is to temporarily offset the generation range constraint by the amount of stored energy at the current time, denoted as $q_{\text{stor},k} = \sum_{i=1}^{N}(q_k^{(i)} - B_{\min})$, so that slow generators can attain a lower generation output level. The adjustment of the generation range requires the RESs to feedback their storage status at each time slot. The instantaneous generation range is then given by

$$g_{\min} - \eta_d q_{\text{stor},k} \leq d_{s,k}/\Delta t \leq g_{\max} - \eta_d q_{\text{stor},k}, \ \forall k, \tag{21}$$

where $g_{\min}$ and $g_{\max}$ also satisfy (19), (20), but can have larger values than in (18). If storage is unavailable, (18) and (21) become the same.

The following optimization problem determines the optimal generation power range $[g_{\min}^*, g_{\max}^*]$ for given forecasts of wind energy and load demand in M time slots,

$$\begin{aligned} &\underset{\mathbf{x},\mathbf{y},g_{\min},g_{\max}}{\text{Maximize}} && W(\mathbf{x}, \mathbf{y}) \\ &\text{Subject to} && (1), (3)-(7), (9)-(13), (19)-(21). \end{aligned} \tag{22}$$

If the forecasts of wind energy and load demand are accurate, Problem (22) determines the optimal performance of the storage-aided generation range adaption scheme.

2) Suboptimal Online Implementation: With generation range adaption, the ramping constraint of the slow generators between consecutive time slots will not be violated even if the information about future wind energy and load demand is unknown. However, if the optimization problem (22) is directly decoupled into each time slot, i.e.,

$$\begin{aligned} &\underset{\mathbf{x}_k,\mathbf{y}_k}{\text{Maximize}} && W_k(\mathbf{x}_k, \mathbf{y}_k) \\ &\text{Subject to} && (1), (3)-(7), (9)-(13), (18)-(20), \end{aligned} \tag{23}$$

the storage would become inactive, since the system tries to minimize the storage operation cost at each time slot. Thus, a key question of online design remains how to effectively operate the storage when realizations of future wind generation and load demand are unavailable.

Although dynamic programming offers a strong mathematical tool in dealing with uncertainty, its high computation complexity is overwhelming for an online scheme. Here, we propose a heuristic storage management scheme for online implementation of the storage-aided generation range method, which guarantees system security during the slow generator ramping process. Our scheme targets a reduced computation complexity in dealing with

Algorithm 1 Suboptimal online scheme: Initialization stage

Initialization: $k \leftarrow 0$;
while $\eta_d q_{\text{stor},k} < \underline{g_0} - d_{\min}$ **do**
  Full charging if storage is not full: $s_{c,k}^{(i)} = e_k^{(i)}$, $s_{d,k}^{(i)} = 0$;
  Stored energy update: $q_{\text{stor},k} \leftarrow q_{\text{stor},k} + \eta_c \sum_{i=1}^{N} s_{ck}^{(i)}$
  Time update: $k \leftarrow k+1$;
end while
Generation range adjustment: $g_{\min} \leftarrow \underline{g_0}$, $g_{\max} \leftarrow \overline{g_0}$

Algorithm 2 Suboptimal online scheme: Normal stage

while $k \leq M$ **do**
  if $d_k - \sum_{i=1}^{N} e_k^{(i)} - d_{s,k-1} \leq R_s^{\max}$ AND $k < M$ **then**
    Charge setting: $s_{c,k}^{(i)} = \beta p_k^{(i)}$, $s_{d,k}^{(i)} = 0$;
  else
    Discharge setting: $s_{c,k}^{(i)} = 0$, $s_{d,k}^{(i)} \geq 0$, while guaranteeing $\eta_d q_{\text{stor},k} \geq \underline{g_0} - d_{\min}$;
  end if
  Decision making for $\mathbf{x}_k, \mathbf{y}_k$ at time k by solving (23) together with charge/discharge settings;
  Stored energy update: $q_{\text{stor},k} \leftarrow q_{\text{stor},k} + \sum_{i=1}^{N} (\eta_c s_{ck}^{(i)} - \eta_d s_{dk}^{(i)})$
  Time update: $k \leftarrow k+1$;
end while

uncertainty compared with the dynamic programming approach. The details of the proposed scheme are shown in Algorithms 1 and 2. The control procedure is divided into initialization and normal stages according to the level of stored energy $q_{\text{stor},k}$. In the initialization stage, the storages are charged to provide enough offset for the generation range of the slow generators such that the slow generators can accommodate the minimum load $d_{\min}$ in case there are no wind energy arrivals. Full charging is preferred if the storage is not full, to speed up the initialization process. Once the desired stored energy is available, the generation range $[g_{\min}, g_{\max}]$ is set to the predefined range $[\underline{g_0}, \overline{g_0}]$ corresponding to current average wind energy and average load demand, and the control procedure transitions to the normal stage. In the normal stage, a heuristic storage management scheme with complementary charging and discharging decisions (based on Proposition 1 by assuming sufficiently large storage size) is applied to extend the effective ramping range and the utilization of the slow generators:

- when the difference between load demand and total wind energy arrival falls into the ramping range of the slow generators, charge at least β $(0 < \beta < 1)$ portion of wind generation $p_k^{(i)}$ into the storage;
- otherwise, discharge is allowed while the remaining energy should be maintained above the minimum offset level $\underline{g_0} - d_{\min}$.

With this heuristic storage operation scheme, optimization problem (23) is solved at the beginning of each time slot for online decision-making for wind energy integration and generator ramp control. The system needs to keep records of the previous generation power. The values of the generation power range $[\underline{g_0}, \overline{g_0}]$ and the charging threshold β are set for different expected, instead of instantaneous, levels of wind energy and load demand. To this end, historical data records of the wind energy and load demand can be used to determine the settings of $[\underline{g_0}, \overline{g_0}]$ (e.g., input historical data into (22)) and β.

IV. Simulation Results

Consider a system with one UC and $N = 20$ RESs. The power load in the system is composed of a basic load of 20 MW, which is time invariant, and a flexible load, which is uniformly distributed in $[0, 40]$ MW [15]. The renewable energy generation at each RES is modeled as an ON-OFF process with a probability of 0.3 for the "ON" state. The timescale of the system is $\Delta t = 5$ min, and $M = 20$ time slots are adopted for the control time horizon. Table I shows the generator configuration at the UC. We assume each RES is equipped with a storage, i.e., $N_s = 20$, with the configuration shown in Table II.

TABLE I
UC Generator Configuration [6].

Generator type	Slow gen.	Fast gen.
Ramp rate (MW/5 min)	$R_s^{\max} = 10$	$R_f^{\max} = 50$
Generation capacity (MW)	$G_s^{\min} = 10$ $G_s^{\max} = 100$	$G_f^{\max} = 60$
Generation cost	$a_s = 0.005$\$/MW^2 $b_s = 60$\$/MW	$a_f = 0.04$\$/MW^2 $b_f = 160$\$/MW

TABLE II
RES Storage Configuration [16].

Efficiency	$\eta_c = \eta_d = 95\%$
Rating (MW/5 min)	$Q_c = Q_d = 200$ kW/sec
Capacity	$B_{\max} = 800$ kWh, $B_{\min} = 0$ kWh
Operation cost	$\rho_c = \rho_d = 7.5$\$/MW^2

The quadratic utility function in (2) is adopted for evaluation. The preference factor of the UC towards renewable energy integration is set to $\delta_d = 60$ and $\alpha_d = \frac{\delta_d}{\mathbb{E}\{\sum_{i=1}^{N} e_k^{(i)}/N\}}$ where $\mathbb{E}\{\cdot\}$ denotes the expectation operation, i.e., the UC's maximal satisfaction is achieved when the wind energy supply is no less than the mean (expected) wind generation level at each RES.

Three offline schemes are evaluated assuming full knowledge of wind energy and load demand: i) integration with *full* generation range (cf. (17)), ii) integration with *adaptive* generation range (cf. the storage-aided generation range adaption scheme in (22)), and iii) maximal integration (denoted as "*max*"), in which the power system maximizes the total amount of integrated wind energy instead of the social welfare. Besides, the proposed *online* suboptimal scheme of generation range adaption (cf. (23)) is assessed assuming forecasts of wind energy and load demand are unavailable. The maximal wind energy integration is considered as the baseline scheme for wind energy integration. To study the benefits of wind energy integration, we set a reference value of social welfare, denoted as W_0^*, as the optimal social welfare of the full generation range scheme without wind energy integration. The difference between the social welfare of each wind integration scheme and W_0^* then defines the social welfare surplus due to wind energy integration.

Figure 3 shows the social welfare surplus per time slot for different wind energy arrival levels. The performances of the offline schemes are compared first. From the figure, maximal wind energy integration achieves the lowest social welfare. This implies, simply integrating as much wind energy as possible can be detrimental to the social welfare since the wind ramps can penalize the operation costs of the power system. Thus, ramp control is necessary to manage wind energy variations and to promote efficient wind energy utilization. Besides, generation range adaption can avoid the risk of ramping violations in slow generators when forecasts of wind energy and load demand are inaccurate. However, restricting the output range of the slow generators results in increased usage of (expensive) fast generators. Thus, the generation range adaption scheme causes a loss in social welfare compared to the full generation range scheme, especially when storage is unavailable. The gap between the adaptive and full generation range schemes is reduced with the aid of storage, as the generation range of slow generators can be effectively extended.

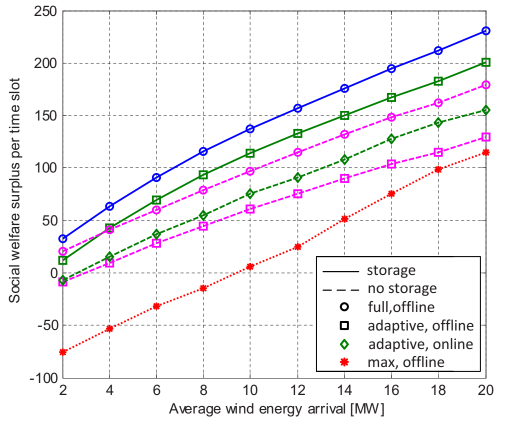

Fig. 3. Social welfare surplus vs. wind energy arrival.

TABLE III

PARAMETERS FOR ONLINE SCHEME ($\overline{g_0} = \underline{g_0} + R_s^{\max}$).

Wind arrivals (MW)	2	4	6	8	10
$\underline{g_0}$ (MW)	22.5	23.4	23.0	22.3	21.2
β	0.7	0.65	0.6	0.3	0.3
Wind arrivals (MW)	12	14	16	18	20
$\underline{g_0}$ (MW)	19.9	18.2	16.5	14.4	12.9
β	0.06	0.03	0.03	0.01	0.01

The proposed online scheme is evaluated with the parameter settings in Table III, where the values for the generation power range $[\underline{g_0}, \overline{g_0}]$ are set to the average values of $[g^*_{\min}, g^*_{\max}]$ in (22) with 1000 realizations of the wind energy and load demand. From Fig. 3, despite the loss of information about future wind energy and load demand, the proposed online scheme outperforms the offline generation range adaption scheme without storage and the maximal integration scheme.

The impact of the storage size on social welfare is investigated in Fig. 4 with 10 MW wind arrivals. If wind energy and load demand are fully known, the social welfare value for the generation range adaption scheme increases faster with the storage size than that for the full generation range scheme, decreasing the performance gap between the two schemes. This is because larger storage size offers more flexibility in extending the generation range of slow generators. However, in the proposed online scheme, the performance gains achieved with increased storage size are limited due to the loss of information about future wind energy and load demand.

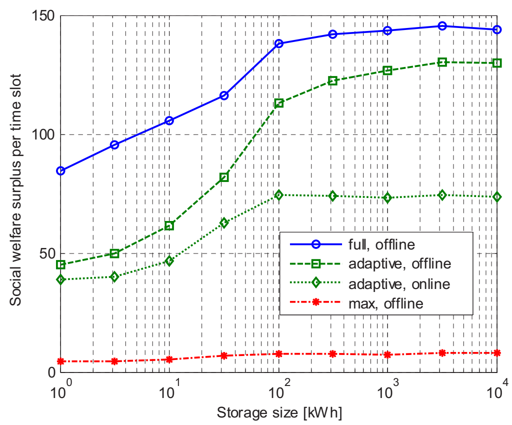

Fig. 4. Social welfare surplus vs. storage size

V. CONCLUSION

In this paper, socially optimal wind generation ramp control with dispersed energy suppliers is investigated. To this end, the pursuits or revenues of both energy suppliers and the utility company are aligned in the social welfare objective. The optimal wind energy integration and generator ramp control are characterized by solving an offline social welfare optimization problem, which requires full knowledge of the future wind energy and load demand. Storage-aided ramp control with generation range adaption is proposed to guarantee power system security during the ramping process of the slow generators when wind energy forecasts are inaccurate. A suboptimal online storage-aided scheme is presented for the case when a forecast for the amount of future wind energy arrival is unavailable. Simulation results show that the offline storage-aided generation range adaption scheme can attain high social welfare, and the performance gaps between adaptive and full generation range schemes are decreased by increasing the storage size. However, suboptimal online scheme suffers a performance loss due to the lack of information about the future wind generation.

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