Wind Integration in Power Systems: Operational Challenges and Possible Solutions

This paper surveys means for integrating wind energy into power systems and suggests alternatives for reliable and cost-effective operation.

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Abstract: This paper surveys major technical challenges for power system operations in support of large-scale wind energy integration. The fundamental difficulties of integrating wind power arise from its high inter-temporal variation and limited predictability. The impact of wind power integration is manifested in, but not limited to, scheduling, frequency regulations, and system stabilization requirements. Possible alternatives are suggested for a more reliable and cost-effective power system operation. New computationally efficient methods for improving system performances by using prediction and operational interdependencies over different time horizons remain critical open research problems.

Keywords: Capacity credit; frequency regulation; grid integration of variable resources; look-ahead scheduling; renewable energy; unit commitment (UC); wind power generation

I. INTRODUCTION

Sustainable energy resources, particularly wind power, are rapidly becoming generation technologies of significance around the world. Due to their high inter-temporal variation and limited predictability, integration of these new resources poses profound challenges to today’s operating and planning practices [1]. This paper puts forward the premise that today’s utility practices, including the supervisory control and data acquisition system (SCADA)-enabled hierarchical operations and control, do not lend themselves to a seamless integration of large-scale wind and other variable resources. Moreover, while most of the operating problems with variable resources experienced so far have been related to the need to temporarily disrupt electricity services, we stress that this is only one aspect of the issues that must be addressed and solved. The other category of problems concerns the missed opportunities to provide cleaner and cheaper electricity services even when it all seems “normal” to the system operator. The tradeoff between different objectives must be understood for effective identification of what needs to be enhanced [2].
The limited predictability and high inter-temporal variations of wind power cause a full spectrum of problems, ranging from shorter term frequency deviations to longer term balancing problems. Fig. 1 provides a summary of likely problems and possible solutions in power system operations related to high wind penetration. The sections are organized based on the operating practices, which imply temporal separation. However, in this paper we emphasize the interdependencies across different time horizons. We assess and quantify these interdependencies using model-based simulations in light of today’s industry practices and future needs. This is followed by proposing possible approaches to systematic cost-effective and reliable utilization of large-scale wind power. The basic premise in this paper is that the boundaries between unit commitment (UC) functions, on one side, and economic dispatch (ED) of committed units, on the other, are no longer pronounced because of the limited predictability of highly variable wind resources. How well the longer term predictions are made will significantly affect the need for fast-responding technologies and the overall system efficiency. Consequently, future dispatch must become a look-ahead function which accounts for inherent inter-temporal constraints of different technologies. Similarly, the boundary between discrete-time dynamics (frequency regulation) and continuous-time dynamics (frequency stabilization) will no longer be as pronounced as in the past.

This paper is organized as follows. Section II presents the state-of-the-art power system scheduling and regulation tools with negligible presence of wind generation. It is suggested that these tools depend on the assumptions that day-ahead hourly demand forecast is quite accurate and the unpredictable component is zero mean noise. These assumptions are contrasted in Section III by stating how the assumptions change with high presence of wind generation and implications of these changes on power system operations. It is suggested that due to hard-to-predict variable wind power generation, the variance of the wind forecast error could be significant and the mean of the error may not be zero. Section IV introduces possible alternative methods for integrating wind power resources in a cost-effective and reliable manner. The new methods are proposed so that high variability is managed by combining as good as possible predictions with the look-ahead scheduling to account for inter-temporal dependencies. Both centralized and more distributed look-ahead scheduling methods are discussed and compared using a small power system example. Moreover, it is recognized that spatially distributed regulation may be needed to manage nonuniform frequency deviations across large geographical areas. Finally, a brief mention of the need for more robust primary control is made. While most of the paper discusses operational challenges, we recognize in Section V major open challenges of planning for integrating large-scale intermittent wind resources. Section VI draws concluding remarks.

II. POWER SYSTEM OPERATIONS WITH NEGLIGIBLE PENETRATION OF WIND POWER

The basic objective of power system operation is to maintain the generation and demand balance, subject to transmission network constraints over a set of plausible contingencies. The two major categories of components are: 1) generators that are dispatchable; and 2) stochastic demand.

Before large amount of variable resources is installed in the power system, the only uncertain type of energy converting components are the loads. Stochastic load models can be characterized as the sum of a predictable term and a noise term [2]. Depending on the prediction time horizon, the variance of the noise term is different. The earliest prediction in operations occurs 24–36 h ahead, assuming constant load value for the duration of each hour. The load can be represented as

\[ L(t) = \hat{L}[H] + \Delta_{LH}(t) \]  

(1)

where \( L(t) \) is the actual load at continuous time \( t \). \( \hat{L}[H] \) refers to the expected constant load value in hour \( H \). We denote \( \Delta_{LH}(t) \) to represent the deviation between the actual load \( L(t) \) and the expected load \( \hat{L}[H] \).

Closer to near real time, the updated load forecast model has a granularity of 10 min. The load model for the same time \( t \) can be represented as

\[ L(t) = \hat{L}[k] + \Delta_{Lk}(t) \]  

(2)

where \( \hat{L}[k] \) refers to the expected load for the 10-min time interval \( k \). \( \Delta_{Lk}(t) \) represents the error term between the actual load \( L(t) \) and the forecasted load \( \hat{L}[k] \).

The state-of-the-art load forecast techniques provide accurate day-ahead and near-real-time demand forecast. Figs. 2 and 3 show a schematic comparison of load...
predictions day-ahead and 10-min ahead. It is typically true that

$$\|L[H]\| \gg \|\Delta_{LH}(t)\|$$

(3)

$$\|\Delta_{LH}(t)\| > \|\Delta_{Lk}(t)\|.$$  

(4)

The decision process concerning which units should be turned on at which generation level is called UC [3]. UC is typically done one day ahead of the actual operating time, and it is based on the information about $L[H]$ for the next 24 h in (1). The updated load prediction $L[k]$, on the other hand, is balanced in the 10-min ahead using ED [3].

A. UC Problem

UC in power systems can be formulated as [4]

$$\min \sum_{H=1}^{24} \sum_{i=1}^{I} C_i(x_{i,H-1}, P_G(H), u_{iH})$$

(5)

subject to

$$\sum_{i=1}^{I} P_G(H) = \sum_{z=1}^{Z} L_z(H)$$

(6)

$$\sum_{i=1}^{I} S_i(x_i, P_G) \geq \hat{L}_z(H) + Re(H)$$

(7)

$$x_{iH} = A_{iH}(x_{i,H-1}, u_{iH})$$

(8)

$$|F(H)| \leq F_{\text{max}}$$

(9)

where

$S_i(x_i, P_G)$: spinning reserve;

$Re(H)$: reserve requirement;

$x_{iH}$: state variable for resource $i$ in hour $H$;

$u_{iH}$: on/off for resource $i$ in hour $H$;

$A_{iH}$: resource function for resource $i$ in hour $H$;

$Z$: set of load zones;

$I$: set of generators;

$F$: vector of line flows;

$F_{\text{max}}$: vector of maximum line flow constraints.

This is a mixed-integer programming (MIP) problem. UC problem originally was solved by Lagrangian relaxation (LR) or augmented Lagrangian relaxation approaches [5], [6]. Recent advances in optimization and computing capabilities make solutions of branch and bound (B&B)-based MIP tractable [7]. Many of the independent system operators (ISOs) are now moving from LR solutions toward MIP solutions for the UC due to typically smaller duality gap and ease of modeling complex constraints [8].

Some ISOs are conducting real-time security-constrained unit commitment (SCUC) which considers the on/off of fast response units [9]. We understand that the industry SCUC practice typically employs a two-stage approach. Stage 1 is a UC for generation without observing transmission network constraints. Stage 2 checks if the results of UC meet the power flow and network constraints. If not, system operators will make the decisions to modify the results of UC until the solution is secure. This is of course indeed suboptimal and not a result of a single SCUC. Particularly bothersome are the convergence problems as the results of the two stages are iterated.

B. ED Problem

The UC decision making is based on the 24–36-h-ahead prediction of hourly system demand. As one gets closer to real time, an updated load forecast is taken into account for performing ED. This usually takes place every 10–15 min. To review the ED, we define the following notations:

$G$: the set of all available generators;

$G_r$: the set of intermittently available energy generators;
The ED problem is then formulated as follows:

\[
\begin{align*}
\min_{\hat{P}_G} & \sum_{i} (C_i(P_{G_i(k)})), & i \in G \\
\text{s.t.} & \sum_{z} P_{G_i(k)} = \sum_{z} \hat{L}_z(k), & i \in G, z \in Z \quad (10) \\
& p_{G_i}^{\min} \leq P_{G_i(k)} \leq p_{G_i}^{\max}, & i \in G \quad (12) \\
& |F(k)| \leq F_{\text{max}} \quad (13) \\
& \sum_{i} R_{Ei}(k) \geq R_{E^T}. \quad (14)
\end{align*}
\]

As shown in the above formulation, conventional security-constrained economic dispatch (SCED) is essentially a static optimization problem. The rates of response of individual units are not explicitly accounted for in the ED problem formulation. There is an implicit differentiation of fast- and slow-responding generation units. The slow responding units, such as nuclear and coal units, are not considered in the set of generators \(G\). Although UC and ED decisions are interdependent, this separation of UC and ED is primarily to reduce the computational burden of mixed integer programming.

To partially capture the interdependency between UC and ED, enhancements of entirely static ED have been proposed. For example, in [13], a dynamic ED is formulated by taking into account the ramping rates as inequality constraints. In this formulation, the ED is formulated as follows:

\[
\begin{align*}
\min_{\hat{P}_G} & \sum_{k=1}^{K} \sum_{i} (C_i(P_{G_i(k)})), & i \in G \\
\text{s.t.} & \sum_{k} P_{G_i(k)} = \sum_{z} \hat{L}_z(k), & i \in G, z \in Z \quad (16)
\end{align*}
\]

While a dynamic dispatch requires more computational effort compared with the static dispatch, the total generation cost resulting from dynamic dispatch is typically lower compared with the static dispatch. It is our understanding that advanced control centers are beginning to utilize more dynamic versions of ED as well [14].

### C. Primary Stabilization and Frequency Regulation

Frequency in alternating current (ac) synchronous electric power systems should be maintained nearly constant at its nominal value to ensure safe and reliable operation. Some of the reasons for maintaining tight control of system frequency are: 1) synchronous machines are designed to operate at nominal frequency, 2) considerable frequency drop can result in high magnetizing currents in induction motors and transformers, and 3) need to meet the manufacturing specifications of turbines [15]. Historically, the system frequency also provided a universal time standard for electric clocks and other devices, but this role for system frequency diminished with the emergence of digital timers based on crystal oscillator circuits [17].

System frequency deviation indicates the imbalance between system generation and load. To maintain the frequency within an acceptable range, the generation must be adjusted in real time to meet hard-to-predict load deviations from the expected values. During normal conditions, frequency is tightly controlled within a narrow band around the nominal frequency. Under abnormal conditions, such as the trip of a large generation unit or the loss of a high-impact transmission line, the frequency should be maintained above a prespecified threshold. Otherwise, under-frequency protection will disconnect large generation and customers will be affected.

There are two types of frequency control in power systems: primary control of individual generating units and secondary control of control areas [18]. Primary control is very fast and intended to compensate continuous imbalances between generation and load. It is implemented by speed governors of conventional thermal and hydro plants. These controllers adjust the power output of generators in response to local frequency deviations. The time frame for primary control action falls between seconds to one minute. An intentional steady-state error in the primary control loop provides for a stable operating point in the absence of secondary control by driving the generators to an off-nominal frequency [15].

Secondary control, often called load-frequency control (LFC) or automatic generation control (AGC), regulates...
power of selected units to return the frequency and interchange power between control areas to scheduled values. Plants that are selected to participate in AGC respond to so-called area control error (ACE) signals from control centers to adjust their megawatt set points. The function of AGC is to drive the system frequency to its nominal value. This is presently done by each control area driving its ACE to zero [16].

D. Role of Reserves in Normal Operations

Corresponding to the operational time-scale separation, the uncertainty of the noise term of load forecast is accounted for in the operational reserve requirements. The plausible contingencies are also taken into consideration in the reserve requirements [19].

III. IMPACT OF WIND GENERATION ON POWER SYSTEM OPERATIONS

Wind power differs from both conventional generation resources and the loads in the following aspects: 1) the wind power is not fully dispatchable as conventional generation resources; and 2) the wind power is not as predictable 24–36 h ahead as the load components are; only very near-term wind prediction is highly accurate.

Mathematically, the day-ahead wind power model for each hour can be represented as follows:

\[ P_{Gw}(t) = \hat{P}_{Gw}[H] + \Delta_{Gwh}(t) \]  

where \( P_{Gw}(t) \) represents the actual wind generation at continuous time \( t \), and \( \hat{P}_{Gw}[H] \) is the expected hourly value of available wind generation in hour \( H \). The difference between the actual and expected wind generation is denoted as \( \Delta_{Gwh}(t) \).

Closer to near real time, a more accurate wind forecast model has granularity of 10 min. The predictive model for wind power output at time \( t \) can be represented as

\[ P_{Gw}(t) = \hat{P}_{Gw}[k] + \Delta_{Gwk}(t) \]  

where \( \hat{P}_{Gw}[k] \) and \( \Delta_{Gwk}(t) \) represent the expected wind generation and forecast error in 10-min time interval \( k \).

The hard-to-predict wind power component \( \Delta_{Gwk}(t) \), however, cannot generally be assumed to be zero-mean white noise [20]. Given the accuracy of the prediction, wind power forecast has the following properties [21]:

\[ \|\Delta_{Gwk}(t)\| \gg \|\Delta_{Gwh}(t)\| \]  

\[ \|\hat{P}_{Gw}[k]\| \gg \|\Delta_{Gwk}(t)\|, \]

Figs. 4 and 5 illustrate the day-ahead hourly and 10-min-ahead wind power predictions in relation to the timing of UC and ED scheduling. Depending on the operational practices, wind power can be treated as an active decision variable, or as a “must-take” negative load component. We illustrate in this paper that if treated simply as a negative load, the cost of integrating large-scale wind power will be too high to be sustainable.

A. Impact of Wind Power Generation on UC

Knowing in advance the predictability of wind power serves different engineering and economic purposes: 1) long-term wind predictability is necessary for adequate investment planning in generation capacity; 2) medium-term wind predictability \( \hat{P}_{Gw}[H] \) in (21) is necessary for good management and maintenance in scheduling of the system; and 3) short-term wind predictability \( \hat{P}_{Gw}[k] \) in (22) is necessary for effective operations planning. This
section is devoted to short-term wind predictability and its value to effective operations and spinning reserve sched-uling, with a focus on UC.

1) Day-Ahead Predictability and UC: Day-ahead predict-
bility (24–36 h ahead) techniques are currently the subject of extensive ongoing research and development [22]. Today, wind power forecasting methods can account for local influences of roughness, obstacles, and stability of wind speeds at the specified height [23]. The forecast can be based on atmospheric high-resolution area models that approximate the physical state of the atmosphere regularly (at 6-h intervals) with initial conditions taken from recent observations. These methods have been used to help system operators with UC. Short-term electricity demand prediction tools are numerous and have been the subject of extensive research and development [24]. For short term, wind power is less predictable than demand, thus the integration of significant wind power requires UC to be carried out more frequently, preferably each time new wind power forecasts are available (currently every 6 h; more often in the future). In Fig. 6, we illustrate a typical wind power forecast.

UC must take wind power forecast into consideration to be efficient. The commitment decisions are very sensitive to wind power forecast when there is considerable wind penetration in the power system. Neglecting wind power forecast (or taking wind power as negligible) is a decision error that may involve unnecessary costs. Making the UC based on bad forecast also leads to decision errors and might be even worse than having no forecast at all [25]. Suppose one makes a day-ahead UC considering that there will be negligible wind power available and this leads to starting a coal-fired power plant. Then, it might happen that there is plenty of wind available and the wind power must be used according to today’s practice. Therefore, since coal-fired power plants could not reduce their power output fast enough, it would be required to turn off the coal-fired units. If one decides to do this, one or more inefficient gas-fired power plants would need to be started, thus leading to increased operational cost. Otherwise, if one decides to maintain the unit committed and curtail wind power, then one wastes the clean wind energy. This scenario highlights the value of wind predictability as the UC is done. This, in turn, supports the basic premise of this paper, which is that not entire available wind power should be sent to load via the grid. Instead, portions of the wind power could be stored locally, and this could determine the value of local storage.

2) Valuation of Wind Predictability in UC: Short-term wind predictability plays an important role in the operational planning context. In operational planning the time horizon and the time resolution of the wind predictability and of the operational planning tasks coincide (completely or to a large extent). This will enable the operational planner to quantify the wind-generated power profile and assess its degree of firmness, i.e., the capacity associated with the expected wind-generated power profile. The wind predictability can lead to two types of savings: savings due to reduced committed thermal capacity and savings due to the operation of more efficient units. The problem of assessing the amount of these savings can be stated as follows.

Given a generation mix, forecast load, reserve and operational requirements, and a (set of) wind power profile(s), evaluate the economic benefit of having predictable wind.

The complexity of the overall problem depends on the level of detail: that should be the same as the one needed for operational planning. This means, for example, that chronological load curves will be used (not load duration curves), and the time resolution will be 1 h or 10–15 min. The operational planning problem will involve hourly (or half-hourly) requirements on energy, and on operational and spinning capacities. These requirements play an important role in ensuring that the load demand is met. Good wind predictability will enable using wind capacity to contribute to the operational and spinning reserve requirements. In what follows we give an example with a horizon of a week that illustrates the differences between optimal UCs with and without accurate wind prediction. The example is set to be small to highlight the nature of the underlying differences.

Consider a power system comprising three thermal power plants as shown in Table 1, where power is expressed in megawatts. Consider a given load profile and a wind power profile during normal operation (no reserve requirements). Suppose that one solves optimal UC in two different situations: 1) neglecting wind capacity and dispatching wind energy as available (no prediction); and 2) considering perfect wind predictability (both energy and reserve). Results from these two problems are presented. Fig. 7 shows power profiles of thermal generation with wind energy and no wind capacity (no wind predictability). The rationale for this commitment is that no wind
Energy was expected at the time of the commitment decision, but the wind energy actually was available and hence accepted. As a result, thermal resources operate at lower levels (lower than those computed at the time of commitment decision). Fig. 8 shows the same power profiles under the assumption that there will be wind-generated energy as predicted.

The savings due to wind capacity, as computed by simulation, are broken down as follows: 12% due to startup savings; 88% due to operating costs savings. In our experiments with different scenarios, the value of wind predictability changed between 0% and 14%, with an average value of 6%. Simulations with hourly resolution to capture the dynamic operating benefits of the wind predictability have indicated a 12% additional benefit when compared with the sole benefit of energy supply. The additional benefit comes from savings in startup costs and mostly from operational savings due to a better UC [26].

B. Impact of Wind Generation on ED

A high level of concern cuts across technical, economic, and environmental policy issues relevant for effective utilization of wind and other variable resources. As already experienced in the case of Bornholm Island [29], it is going to be extremely difficult to integrate variable resources in the existing electricity markets in a sustainable way, once the subsidies are gone. The key factor for this complexity comes from the fact that today’s dispatch does not have good mechanisms to value rate of response or to manage inter-temporal uncertainties at value. In recent years there has been a variety of research efforts addressing the impact of large-scale variable wind generation on system ED. In [30], the value of prediction of wind in reducing the system-wide emission as well as generation cost is quantified assuming static dispatch. The cost of implementing static dispatch is high, especially in systems with high wind penetration. Novel approaches are required to reduce the ED cost due to high wind penetration.

C. Impact of Wind Generation on AGC

With the expansion of installed wind power capacity, significantly more regulating reserve will be required to balance both load uncertainties and high wind power variations. In conventional practice, the fast-responding AGC units react to ACE signals dispatched from the control center. ACE represents load-generation mismatch for a control area. The information regarding frequency and tie-line flow errors is bundled into ACE signals, simplifying the task of regulating frequency and inter-area flows by responding to a single control input [31]. Based on the premise that inter-area effects are typically weaker than intra-area effects, all generators within an area are assumed to be rotating at the same speed. This is equivalent to having a numerically identical frequency error throughout an area. Such an assumption may not be well suited for systems with high wind penetration. One may observe potentially larger imbalances at locations where installed wind capacity is high. The required regulation units and frequency quality standards can vary spatially within a control area. This spatial variation necessitates need-based allocation of regulating reserve, requiring unbundling of the control input down to the generator level. In general,
the underlying principle of lumped ACE input does not lend itself to spatially differentiated frequency regulation. This is a critical issue that needs to be revisited in systems with generation mix comprising diverse variable resources. There have been studies on the impact of wind integration on conventional AGC in real-world systems. For instance, analysis in [32] shows that the integration of large-scale wind generation requires novel frequency regulation and load following mechanisms for the California ISO.

D. Impact of Wind Generation on Frequency Stabilization

Increasing the ratio of wind power to traditional generation can generally degrade fast frequency response. When a significant amount of wind energy penetrates the power system, very fast fluctuations in wind generation need to be compensated in addition to load variations, thus increasing the amount of control effort required to stabilize system frequency. Several studies have evaluated the impact of large-scale wind power integration on frequency control performances. Luo and Ooi proposed a transfer function method to estimate the frequency deviation caused by continuous wind power fluctuation [33]. In a further collaboration, they extended this approach to estimate the level of wind power penetration as limited by frequency deviation in [34]. The impact of wind power minute-to-minute variations on power system operation is studied in [35], where wind power variations are decomposed into slow, fast, and ramp components to assess the influence of each component on system operation.

Moreover, modern variable speed wind turbine generators are often isolated from the grid by power electronic converters, thus contributing almost no inertial response to the overall power system [36], [37]. Power electronic converters decouple the rotational speed of wind generators from the grid frequency and allow variable speed operation possible. Therefore, there is no direct relationship between the power output of such wind turbine generators and the grid frequency, unless additional control loops are introduced.

If more synchronous machines are displaced by wind generation, the system inertia decreases making power system more sensitive to generation-load imbalances. This is particularly true for standalone power systems such as the Ireland power system [36] and Hawaii power system [38], where the system inertia is relatively small and no interconnection can provide additional support in case of a contingency, such as a sudden loss of generation. Consider the following standalone power system shown in Fig. 9. The thermal units only have primary control and the wind plants are of variable speed types that contribute no inertia response and frequency control. The system load is 1000 MW and thermal plants have a total capacity of 1200 MW as the base case with no wind generation. As the wind power generation increases, equal capacity of thermal plants is subtracted from the base case of 1200 MW. For example, if the wind power generation is 300 MW (30% of the total load), the thermal plants have a capacity of 900 MW and generate 700 MW to support the rest of the 1000-MW load. The tested disturbance is a 10% step load increase. Fig. 10 shows that as the percentage of wind generation increases by replacing conventional thermal units, it will result in lower minimum frequency and higher maximum rate of change of frequency (ROCOF).

IV. POSSIBLE ALTERNATIVE METHODS FOR INTEGRATING LARGE-SCALE WIND POWER

Section III presented the operational challenges in power systems due to the increasing presence of variable wind energy resources. In this section, we propose that by incorporating short-term wind forecast and by utilizing more advanced hardware/software control of wind generators, operators could adjust the predictable component of wind power output more reliably and more efficiently than it is currently done, and/or store portions of wind power locally, if needed. In this section, alternative means of power system operations with significant presence of wind energy are presented keeping these technological options in mind.
Given the temporal and spatial complexities created by highly varying resources, we first discuss possible means of managing inter-temporal dependencies. More reliance on prediction and look-ahead decision making by the system users is envisioned. In particular, forward scheduling functions such as more frequent UC and look-ahead dispatch are described. In the second part of this section, we revisit closed-loop balancing functions such as frequency regulation and system stabilization [51]. This is done with a full recognition of the fact that frequency regulation could use both generation and load resources. Also, with the penetration of small resources, the closed-loop balancing is likely to move closer to distributed groups of system users. To implement these it will require higher spatial granularity in designing and valuing frequency regulation at the level of small balancing authorities created by the portfolios of system users. In fact, once a single control area decomposes into a set of many small balancing authorities as predicted sometime ago in [51], we suggest that regulation must be done by such small balancing authorities. This would make it feasible to implement frequency regulation schemes which are based on spatially different frequency measurements by means of sensors such as phasor measurement units (PMUs). Coordinating different resources within small balancing authorities could be implemented using many smart grid technologies by the users themselves. All these small balancing authorities ultimately contribute to frequency regulation within what once used to be a control area (utility).

A. Methods for Enhancing UC

One major challenge facing system operators is to commit units in systems with high wind power penetration due to considerable uncertainty. A number of possible solutions has been proposed in the literature. For example, in [11] and [12], stochastic UC is formulated for operations planning with significant wind generation. This requires that the UC solution be robust for accommodating: 1) low wind power profiles when wind was expected to be high; and 2) high wind power profiles when wind was expected to be low. Robustness is reflected in the UC being flexible enough to accommodate wind variations, without emergency commitment or emergency decommitment. A formulation of such UC problem should include the following two operational reserve requirements:

\[
\begin{align*}
\sum_{i=1}^{I} R^{U}_{iH}(x_{iH}, P_{iH}) & \geq P_{iH}^{\text{max}} \quad (25) \\
\sum_{i=1}^{I} R^{D}_{iH}(x_{iH}, P_{iH}) & \leq P_{iH}^{\text{min}}. \quad (26)
\end{align*}
\]

Equations (25) and (26) define the reserve requirement for low and high wind scenarios, respectively. They emphasize the need for UC solution to have sufficient reserve committed in order to supply the demand if the wind power profile is lower than expected (with reserve requirement \(P_{iH}^{\text{max}}\) in hour \(H\)), as well as supply the demand when the wind power profile is higher than expected (with reserve requirement \(P_{iH}^{\text{min}}\) in hour \(H\)).

In an electricity market environment, the operating reserve requirements are handled as commodities. \(\mu_{iH}^{U}\) and \(\mu_{iH}^{D}\) represent ramp-up and ramp-down reserve bids by the generators. A market-based UC which ensures sufficient reserve at value subject to reserve requirements (25) and (26) would be formulated as follows:

\[
\begin{align*}
\max_{\lambda_{iH}} \sum_{H=1}^{24} \sum_{i=1}^{I} \left( \lambda_{iH} P_{iH}^{U} + \mu_{iH}^{U} R^{U}_{iH}(x_{iH}, P_{iH}) \\
+ \mu_{iH}^{D} R^{D}_{iH}(x_{iH}, P_{iH}) - C_{iH}(x_{iH-1}, P_{iH}, u_{iH}) \right). \quad (27)
\end{align*}
\]

Based on this formulation, one could create a reserve market to establish adequate hourly or near-real-time prices for the ramp-up and ramp-down spinning reserves [27]. If such a market is available, the requirements for spinning reserves could be lowered by giving disincentives to wind generators to deviate from their forecast. As an example, recently, New York ISO has proposed to impose penalty on wind farms if they fail to follow the dispatch down signals [28]. Fundamentally, it would be possible to reduce operational reserve requirements utilizing better predictability and solving UC problem more frequently as the wind power forecast becomes more accurate.

B. Methods for Enhancing ED

We present here a look-ahead ED approach in support of variable generation resources [39]. Based on short-term prediction of power output from the intermittent resources, the look-ahead methods optimize over a pre-specified time horizon the available generation with the objective of minimizing the total production cost. This method is compared with the present static ED which treats variable resources as uncertain negative loads. We suggest that the proposed look-ahead approach could reduce the total generation cost by explicitly accounting for the rate of response of different types of generators. In Sections IV-B1 and B2, we summarize the centralized and distributed look-ahead dispatch algorithms. Centralized look-ahead dispatch is a method which accounts for inter-temporal constraints at the control center level. On the other hand, distributed look-ahead dispatch relies on look-ahead inter-temporal optimization for the assumed system conditions by both power producers and consumers. Most typically centralized look-ahead dispatch is used by vertically integrated utilities. Similarly, distributed look-ahead dispatch lends itself to the competitive electricity market environment.
1) Centralized Look-Ahead Dispatch: A centralized look-ahead dispatch provides means of incorporating intertemporal dependencies of intermittent wind resources into the ED procedure while accounting for the line flow limits (congestion). This is in contrast with the typical industry practice of SCED, which is based on static optimization which determines the optimal generation output for the set of units that are on from the UC decision process. Due to the increase of variable resources, several major ISOs such as the Pennsylvania–New Jersey–Maryland ( PJM ) ISO and the Midwest ISO (MISO) have begun to explicitly model the inter-temporal constraints (e.g., ramping) in their look-ahead dispatch models [9]. As an example, the formulation of the centralized look-ahead dispatch can be represented as follows [39]:

\[
\begin{align*}
\min_{P_G} & \sum_{i=1}^{K} \sum_{t=1}^{T} (C_i(P_G(t))), \quad i \in G \\
\text{s.t.} & \quad \sum_i P_G(t) = \sum_h \hat{L}_h(t), \quad i \in G, z \in Z \\
& \quad \hat{L}_z(t) = f_z(L_z(t-1)), \quad z \in Z \\
& \quad \bar{P}_G^{\max}(k) = g_k(\bar{P}_G^{\max}(k-1)) \\
& \quad \bar{P}_G^{\min} \leq P_G(k) \leq \bar{P}_G^{\max}, \quad i \in G_r \\
& \quad \bar{P}_G^{\min} \leq P_G(k) \leq \bar{P}_G^{\max}, \quad i \in G \setminus G_r \\
& \quad |P_G(k+1) - P_G(k)| \leq R_i, \quad i \in G \\
& \quad |F(k)| \leq F^{\max} \\
& \quad \sum_i R_{e_i}(k) \geq R e^T. \quad (36)
\end{align*}
\]

This formulation explicitly considers the output of intermittent resources as decision variables. Therefore, it optimizes the use of generation including direct management of intermittent resources, whose unused output could be stored locally. Otherwise, even without storage, it is possible to directly control how much of wind power gets converted into electric power.

2) Distributed Look-Ahead Dispatch: In most electricity markets, individual power plants submit bid functions to the system operator, then the ISO clears the market by maximizing the social welfare while observing the transmission constraints. Therefore, a look-ahead ED problem can be formulated as a two-stage problem. Each power producer maximizes its own profit by taking into consideration its ramping constraints and available output capacity. Instead of doing a static profit maximization over the next time interval, each power producer maximizes the expected profit over a look-ahead time horizon (e.g., 24 h).

The objective of each power plant is to solve the following optimization:

\[
\begin{align*}
\max_{P_G(k)} & \sum_{i=1}^{K} (\lambda_i(k) * P_G(k)) - C(P_G(k)) \quad (37) \\
\text{s.t.} & \quad \lambda_i(k) = \lambda_i(h), \quad \text{if } k \text{ in the hour } h \\
& \quad \bar{P}_G^{\max}(k) = g_k(\bar{P}_G^{\max}(k-1)) \quad (39) \\
& \quad \bar{P}_G^{\min} = h_k(\bar{P}_G^{\min}(k-1)) \quad (40) \\
& \quad \bar{P}_G^{\min} \leq P_G(k) \leq \bar{P}_G^{\max}, \quad j \in G \\
& \quad |P_G(k+1) - P_G(k)| \leq R_i, \quad i \in G. \quad (42)
\end{align*}
\]

As a result of the optimization (37)–(42), each individual power producer creates its bids according to longer timescale price signals (e.g., day-ahead power price). The outcome of this optimization is the pair of price and desired power output ($\lambda_i$, $P_G(k)$). By perturbing the expected price up and down by $\%$ (e.g., $\pm 5\%$, $\pm 10\%$), each power producer can construct the bidding function for the range of prices.

At the second stage, the ISO collects the submitted bids and solves SCED as follows:

\[
\begin{align*}
\min_{P_G(k)} & \sum_{i=1}^{K} (B_i(P_G(k))), \quad i \in G \quad (43) \\
\text{s.t.} & \quad \sum_i P_G = \sum_z \hat{L}_z(k), \quad i \in G, z \in Z \\
& \quad \hat{L}_z(k) = f_z(L_z(k-1)), \quad z \in Z \\
& \quad |F(k)| \leq F^{\max} \\
& \quad \sum_i R_{e_i}(k) \geq R e^T. \quad (47)
\end{align*}
\]

As an illustration, three scenarios of ED are simulated in a modified IEEE 12 bus system, namely, conventional static ED, centralized look-ahead ED, and distributed look-ahead ED. The detailed parameters of this system are obtained from [39]. The system consists of five generator farms with very low short-run marginal cost. Ten-minute-ahead available wind power prediction is obtained from [39]. Ten-minute load data is obtained from New York ISO [42] and is scaled to fit the size of this system. Fig. 11 shows the actual system load and the net system load after subtracting outputs from the available wind power. It can be seen that the net load is more volatile than the original system load.

Table 2 summarizes the performances of the three algorithms. The centralized and distributed look-ahead
ED methods reduce total generation cost by 9.5% and 6.1%, respectively. The computational time of the distributed look-ahead algorithm is 78% faster than the centralized look-ahead algorithm. Figs. 12 and 13 show the outputs from coal unit 5 and natural gas unit in the three scenarios. Fig. 14 shows the differences of wind power from unit 3 computed using conventional ED and look-ahead dispatch algorithms. In contrast to the conventional static dispatch which takes the entire available wind power in real time to the grid, the centralized and distributed look-ahead dispatch yield on average 5.69 and 1.71 MW lower real-time wind power sent to the grid, respectively. Despite the fact that the seemingly “free energy” is not fully injected into the grid, the overall system generation cost is reduced in the proposed look-ahead dispatch. This is due to the fact that by smoothing out high inter-temporal changes from the wind generation, the generation from the fast responsive yet expensive natural gas unit is also reduced. This reduced amount of wind-generation injection to the grid could either be stored locally or curtailed. Overall, the distributed look-ahead ED algorithm is computationally comparable with conventional dispatch algorithm while approaching the cost saving by the centralized look-ahead ED algorithm.

In summary, look-ahead dispatch approach is more cost effective than static dispatch in power system scheduling because it explicitly values the near-term wind power prediction and differentiates the rate of response from different generation technologies. The proposed look-ahead scheduling approach is implementable by both centralized and decentralized industries. The value of good short-term forecast of variable resources is manifested in the total generation cost savings. Consequently, the proposed algorithm results in lower total generation cost than the conventional ED. Further cost reduction is possible through combining demand-side responsiveness with the

Table 2 Performance of the Three Algorithms With Congestion

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Computational Time</th>
<th>Total Gen Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional ED</td>
<td>182 seconds</td>
<td>$601.2 Million</td>
</tr>
<tr>
<td>Centralized Look-ahead ED</td>
<td>1021 seconds</td>
<td>$544.9 Million</td>
</tr>
<tr>
<td>Distributed Look-ahead ED</td>
<td>221 seconds</td>
<td>$564.1 Million</td>
</tr>
</tbody>
</table>

Fig. 11. Load versus load minus expected wind generation.

Fig. 12. Coal unit 5 generation in three scenarios.

Fig. 13. Natural gas unit generation in three scenarios.
look-ahead dispatch [43]. The introduction of look-ahead dispatch again illustrates the effects of accounting for inter-temporal variations. Future enhancements are needed to include greenhouse gas emission effects [40].

C. Methods for Enhancing Frequency Regulation

Wind power penetration increases hard-to-predict real power supply and demand imbalances. Both continuous and second-by-second imbalances could jointly lead to quasi-stationary frequency deviations (spatially nonuniform) across very large geographical areas. This begins to create the case for more distributed frequency regulation. These imbalances must be compensated by the closed-loop frequency regulation instead of relying on UC/ED which require forecast. For the purpose of differentiating frequency regulation of units at different locations, we suggest considering a more distributed AGC formulation in contrast to today's ACE-based AGC design. An earlier introduced concept of spatially differentiated frequency regulation could be applied for this purpose [44]–[46]. Also more accurate fast synchronized PMU measurements could be used to detect frequency deviations in different locations, which was not possible in the past. This concept is potentially more complex to implement since it requires coordination of spatially distributed frequency measurements. However, the concept lends itself to distributed frequency regulation by many smaller balancing authorities. These balancing authorities are not necessarily the same as today's control areas. If frequency regulation is done by many balancing authorities, spatially distributed frequency regulation becomes straightforward to implement.

In contrast to the ACE control signals based on spatially averaged frequency deviation in each control area, the control structure proposed in [44]–[46] is based on localized frequency measurements in each small balancing authority. Such mechanism requires minimal regulation from the system operator [46]. It is logical to design a control input based on frequency deviation rather than the real power imbalances. A control input directly regulating real power imbalances cannot ensure differentiated frequency standards. This is due to typically very low value of generators' frequency sensitivity with respect to power output, so-called droop characteristic (see the Appendix).

Figs. 15 and 16 compare frequency response of a conventional generator in a 5-bus system [47] subject to 1) no wind penetration, and 2) 25% wind penetration. The ACE signal is updated every 4 s. As shown in both figures, the nonzero mean of wind power prediction error creates nonzero frequency deviations. The proposed enhanced frequency regulation performs better than the ACE-based AGC in terms of staying within frequency deviation bounds. The design of an ancillary service market to value spatially differentiated frequency regulation remains an open technical and regulatory research question.

D. Robust Control Approach to Frequency Stabilization

Improving primary frequency control for power systems with high wind power penetration is an active area of research. One approach to improve frequency performance in the face of increased wind generation is to introduce robust control on the conventional generators. Bevrani illustrates the use of robust control design to AGC [53]. $H_\infty$ methods can be used to synthesize controllers to achieve robust performance and/or stability in the presence of bounded uncertainties, disturbances and noises [54]. The $H_\infty$ control technique is applied to design new controllers for conventional plants to better attenuate continuous wind power fluctuations [55]. This is illustrated through the following example. Consider the same power system in Fig. 9, with one thermal plant and one wind farm supplying a load of 1000 MW. The thermal plant has rated power of 700 MW, and it is operating at
500-MW output. The wind farm operates also at 500-MW output, with ±25-MW (5%) power fluctuation. For the time scale of primary frequency control, we assume that reactive power is compensated locally and bus voltages are tightly controlled, so that we only need to consider real power balance equations for the network. The wind power fluctuation is characterized by its frequency spectrum. For a specific system, such information can be obtained from measured typical wind power data. The frequency spectrum of wind power fluctuation is then used in the $H_{\infty}$ problem formulation as the characterization of exogenous disturbance. The resulting robust controller can effectively narrow the band of frequency deviation caused by wind power fluctuations as shown by the response of the system frequency in Fig. 17. Redesign of the primary controllers for conventional generators is limited, however, by inherent rate limits in the actuation. Further research is also needed to design effective decentralized and/or distributed controllers for real-scale power systems.

Researchers have also been investigating methods for implementing primary control on the wind generation itself. Control schemes that allow wind turbine generator to participate in inertial response and primary frequency control are proposed in [36], [37], and [56]–[60]. The main idea is to make the active power control of the wind turbine generators dependent on the network frequency through supplemental control loops. The capability of voltage-source converters to regulate the real power output of the wind turbine generator to smooth the wind power fluctuation is investigated in [61]. Apart from the control on the wind-generation side, strategies have also been proposed to improve frequency control for systems with high wind power penetration using battery systems [62], distributed generation [63], super capacitors [64], superconducting magnetic energy storage systems (SMES) [65], flywheels [66], and energy storage systems (ESS) in general [67].

In summary, it is clear that increasing penetration of wind power into power systems can lead to wider variations in frequency under normal operating conditions and less capability to respond effectively to large disturbances. Although there appear to be several alternatives for dealing with the effects of wind generation on primary frequency regulation, more research is needed to determine what will be most effective for specific systems. There is also a need to rethink the interactions between primary and secondary control, addressed in the following section, since frequency disturbances due to wind generation tend to fall within the traditional time-scale boundary between primary and secondary control action.

V. PLANNING ISSUES IN SYSTEMS WITH HIGH WIND PENETRATION

It has become increasingly clear that high wind power uncertainties are likely to affect system performance in major ways. In this paper, we have discussed in considerable detail the importance of short-term wind prediction in support of look-ahead UC and ED functions. We suggested that some solutions are plausible.

However, a much harder challenge concerns planning of future energy systems with large intermittent resources. Fundamentally, long-term demand forecast is very difficult. The long-term forecast of wind power to the level of granularity needed to count on its availability and not building conventional generation remains largely an unsolved problem. Some recent progress can be found in [68]–[70]. A summary of this work is presented in the remainder of this section.

Capacity evaluation is an important aspect in long-term system planning. Renewable energy resources, such as wind, solar (especially photovoltaics), and run-of-the-river small-hydro (mini-hydro), are often considered as

![Fig. 16. Frequency deviation of generator 1 with spatially differentiated frequency regulations.](image1)

![Fig. 17. Frequency deviation caused by wind power fluctuations.](image2)
energy resources with a residual capacity value. If the capacity were zero or considered as zero then conventional resources (thermal and reservoir-hydro resources) would be needed to guarantee the satisfaction of the power demand. On the other hand, if the capacity were nonzero, then some of those conventional resources would not be needed; hence they would not be required in the expansion plans. Thus, considerable investment costs could be spared.

The approaches taken can be classified into two broad categories: chronological simulation approaches and probabilistic approaches. In some of these approaches, the focus is on load modifications caused by the renewable resource. The impact of the renewable resources is measured by running a resource planning model for the modified load, which yields the corresponding capacity and energy values for the resource. Indeed the capacity value in American dollars of a renewable resource can only be calculated based on the value of the capacity of conventional resources it displaces or avoids. However, the value in megawatts of the resource capacity can be calculated based solely on the behavior of the resource and on the behavior of the demand. In this section, we will focus on assessing the value of capacity in megawatts of wind resources.

A. Capacity Credit

The problem of determining the value of capacity can be formulated as a probabilistic problem, but needs to use simulation for the computation of complex distribution functions such as residual demand distribution and the power distribution functions of various resources. Suppose that 1) the wind speed $V$ at the time of peak demand follows a Weibull distribution $W(\mu^V, \sigma^V)$; 2) the peak demand $D$ follows a normal distribution $N(\mu^D, \sigma^D)$; and 3) the mapping $M$ of the wind speed $V$ into the power output by the wind resources $O$ is known.

Let $R$ represent the capacity of the conventional resources and the reliability level (e.g., $\alpha = 96\%$) at which the peak demand $D$ should be satisfied. Thus, one can write $P(R - D \geq 0) \geq \alpha$. The value of capacity $c$ is the difference between two quantities $r_1$ and $r_2$. $r_1$ represents the value of $R$ such that $P(r_1 - D \geq 0) = \alpha$; $r_2$ represents the value of $R$ such that $P(r_2 + O - D \geq 0) = \alpha$. Note that $(D - O)$ is the residual demand and the value for the capacity credit in megawatts can be computed by simulation analysis of the residual demand alone.

B. Evaluating Wind Capacity

The values of $r_1$ and $r_2$ can be computed through simulation by sampling $V$ and $D$ and finding the capacity as $c = g(\alpha) - h(\alpha)$, where $g = \text{inv}(F_D(r))$ and $h = \text{inv}(F_{D-O}(r))$. inv stands for inverse function and $F$ represents cumulative distribution function, i.e., $F_X(x) \equiv P(X \leq x)$.

Results of the simulation for different conditions show that the wind peak capacity value decreases significantly with wind installed capacity for the same system, and then saturates. Fig. 18 illustrates this. The figure shows a very fast decrease in capacity that saturates at a value of about 2%; the initial value is over 20%. Three curves are presented: the middle curve is for a reliability level of 96%, $\alpha = 0.96$; the upper curve is for a reliability level of 94%; and the lower curve is for a level of 98%.

Results also show the following wind capacity properties: 1) wind peak capacity increases as the standard deviation of the peak demand increases; 2) wind peak capacity increases as the mean of wind speed increases; and 3) wind peak capacity tends to increase as the standard deviation of the wind speed decreases.

Results of sensitivity analysis illustrate that: 1) wind peak capacity increases as the standard deviation of the peak demand increases; 2) wind peak capacity increases as the mean of wind speed increases; and 3) wind peak capacity tends to increase as the standard deviation of the wind speed decreases.

Main results indicate that the wind peak capacity value decreases significantly with wind installed capacity (in percentage of the peak demand). However, these results were obtained for wind resources considered as one single resource. If wind resources are distributed geographically (as they are), the standard deviation of the wind speed tends to decrease, which implies an increase in the wind peak capacity as compared to the results shown. A more accurate assessment of the capacity credit for a new wind power plant should involve comprehensive simulation of all the system resources including wind cross correlations. That approach would give more accurate results at expense of less insight.
C. Capacity Planning

For higher wind power penetration, the capacity credit tends to be lower as a percentage of the wind installed capacity (Fig. 18). Thus, planning is only affected as the capacity requirements are discounted by the amount of wind capacity credit (Section V-B). For example, for a reliability level of 96% and a 25% of wind installed capacity, one can discount an amount of about 5% of wind installed capacity. That is the capacity credit to meet the highest peak in demand. Smart grid technologies can improve the amount discounted by providing the means to reduce demand at its highest peak in case the wind resources are actually at only a 5% level.

Thus, investment planning for high wind penetrations should consider investments in smart grid technologies as an added source of capacity. These technologies comprise real-time pricing, load control, and distributed generation control. These may contribute to large amounts of capacity and are highly flexible, as opposed to the investments in conventional based-load power plants. If the problem is strictly a capacity problem as originated by a high level of penetration of wind resources, and not an energy problem, then investments in conventional based-load power plants are not good investment options.

VI. CONCLUDING REMARKS

In this paper, we provide a survey of recent efforts toward integrating large-scale variable wind energy resources into power systems. It is described that the path toward high presence of renewable wind-generation portfolio will pose profound challenges to today’s operations in terms of both efficiency and reliability. The fundamental causes are: 1) higher inter-temporal variation from wind generation; and 2) the difficulty of predicting wind generation with satisfactory levels of confidence. These attributes of wind power generation bring about challenges to the existing scheduling, regulation, and stabilization methods and algorithms.

We suggest that a multitemporal model-based systematic approach is needed for achieving the goal of integrating and utilizing large amount of wind power in a cost-effective and reliable manner. By designing more robust primary stabilization and frequency regulation, frequency variations caused by the hard-to-predict wind fluctuations could be reduced. Moreover, by taking into account the value of wind predictability, look-ahead scheduling and UC reduce the total generation fuel cost.

The future of power system generation mix will likely have more significant portions of variable wind generation. This opens up new research opportunities for not only more advanced design of wind turbines and more accurate prediction of wind generation, but also for a more systematic approach to the operations and planning in future electric energy systems. The interdependencies between operations across different time horizons need to be accounted for more rigorously when designing new algorithms for efficient and reliable integration of large-scale wind-generation resources.

APPENDIX I

DEPENDENCE OF MULTITEMPORAL RESPONSE RATES ON POWER PLANT DYNAMICS

As generation technologies change, in order to decide on the type of units capable of participating in AGC, ED, UC, and/or stabilization, it is important to understand basic relations between the physical parameters of the generator–turbine–governor (G–T–G) units and their specifications in terms of ramping rates, droop characteristics, and alike. In this Appendix, we start by briefly reviewing the basic dynamics of a conventional G–T–G set, and derive mathematical expressions for its droop characteristics and ramping rates. Similar derivations are needed for future generation resources to more accurately assess their ability to participate in scheduling, frequency regulation, and stabilization.

A typical design of a conventional generator with its prime mover (turbine of some type) is shown in Fig. 19.

The basic dynamics of a conventional generator–turbine set with its governor as a primary controller can be restated here for completeness

\[
\begin{align*}
\dot{\omega}_G + D\omega_G &= P_T + e_Ta - P_G \\
\dot{P}_T &= f_1(P_T, K_a) \\
\dot{a} &= f_2(a, \omega_G, \omega_G^{\text{ref}})
\end{align*}
\]

where \( P_T \) and \( P_G \) are the mechanical and electrical real power. \( J, D, T_u, \) and \( T_g \) are the moment of inertia of the generator, its damping coefficient, and the time constants of the turbine and the governor, respectively. The state
variables \( \omega_C \) and \( a \) correspond to the generator frequency and the valve opening, respectively. The governor is the local primary controller intended to stabilize frequency to the desired set point \( \omega_C^{\text{ref}} \).

Depending on the purpose of the G–T–G model, different approximations are made. For example, for UC and ED, a notion of ramping rate \( R \) of a G–T–G unit is routinely used as it is done in UC and ED. Similarly, a notion of droop characteristic \( \Sigma \) is used when attempting to use different generators for frequency regulation. In the following sections, we will review the key assumptions and parameters characterizing the G–T–G unit’s ability to participate in frequency stabilization, AGC, ED, and UC.

### A. G–T–G Model Relevant for Frequency Stabilization

For purposes of small signal analysis and frequency stabilization, consider a linearized model of (48)–(50) around an equilibrium operating point

\[
\begin{align*}
J & : \Delta \omega_C + D \Delta \omega_C = \Delta P_T + e_T \Delta a - \Delta P_G \\
T_s & : \Delta \dot{P}_T = - \Delta P_T + K_t \Delta a \\
T_g & : \Delta \dot{a} = - r \Delta a - \Delta \omega_C + \Delta \omega_C^{\text{ref}}.
\end{align*}
\]

This linearized model is typically used for small signal analysis and system frequency stabilization.

### B. Droop Characteristic Relevant for AGC

The G–T–G model relevant for frequency regulation should capture the quasi-stationary changes in frequency at the sampling rate of AGC, which is typically at 10 s. It assumes that the transients between these samples are stabilized using primary governor control. This allows one to set all the \( x_G = 0 \) where \( x_G = [\Delta \omega_C \ \Delta P_T \ \Delta a]^T \) and derive relevant quasi-stationary relations.

In this section, we review the so-called droop characteristic as a quasi-stationary rather than commonly used algebraic concept. With the assumption that the transients are already stabilized for the time horizon of AGC, one can derive the sensitivity of the steady-state frequency with respect to the real power output of a G–T–G unit, when the frequency setting is kept constant (deviation \( \Delta \omega_C^{\text{ref}} = 0 \)). This sensitivity is the definition of droop characteristic \( \Sigma \)

\[
\Sigma = \left[ \frac{\Delta \omega_C}{\Delta P_G} \right]_{\Delta \omega_C^{\text{ref}} = 0} = \frac{r D_G + K_t + e_T}{r}.
\]

\( \Sigma \) is critical because the objective is to bring \( \Delta \omega_C \) back to zero by changing \( \Delta P_G \). A more detailed derivation of relationships for AGC can be found in [19, ch. 13].

### C. Ramping Rate Relevant for ED/UC

In this section, we introduce one possible way of interpreting ramping rates typically used in ED/UC, starting from the actual dynamical model of a G–T–G unit (51)–(53). A similar derivation of ramping rates is not available in any of the references familiar to us.

The ramping rate of a G–T–G set is typically specified at the time scale of 10 min. By defining discrete time index \( (k) \) at the sampling rate of 10 min, we can define the unit ramping rate as follows:

\[
R \triangleq \max(\Delta P_T(k + 1) - \Delta P_T(k)).
\]

The transients of the G–T–G set are assumed to be stabilized much faster than the 10-min sampling rate, i.e.,

\[
\begin{align*}
\dot{x}_G(k+1) & = 0 \\
\dot{x}_G(k) & = 0.
\end{align*}
\]

Between two consecutive time indices, the change of power output is controlled by the change of frequency set point \( \Delta \omega_C^{\text{ref}}(k) \). Physically, there is a limit on how large the frequency set point can be between two consecutive time samples, which is defined as \( \Delta \omega_C^{\text{ref max}} \). By applying maximum frequency set point \( \Delta \omega_C^{\text{ref max}} \) into the dynamical model (51)–(53) between two time steps, one can obtain

\[
\max(\Delta P_T(k + 1) - \Delta P_T(k)) = \frac{K_t}{r} \Delta \omega_C^{\text{ref max}}.
\]

Therefore, the ramping capability of a G–T–G unit with 10-min interval can be represented as

\[
R = \frac{K_t}{r} \Delta \omega_C^{\text{ref max}}.
\]

Coefficient \( K_t \) reflects the rate of conversion for different energy sources (steam \( \neq \) gas \( \neq \) hydro). Coefficient \( r \) reflects the rate at which governor can respond to the frequency deviations. It is the combined effect of the three parameters in (60) that determines the actual ramping rate.

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REFERENCES


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