INVITED PAPER

The Potential of Intermittent Renewables to Meet Electric Power Demand: Current Methods and Emerging Analytical Techniques

This paper provides a framework for understanding the body of literature that has been devoted to the behavior and reliability of intermittent renewables, and discusses recent grid integration analyses within this framework.

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ABSTRACT | Renewable electric power sources like wind and solar have been shown from a resource perspective to have significant potential to reduce the carbon dioxide emissions associated with the electric power sector. However, the intermittency of these resources is often cited as a barrier to their large scale integration into the grid. In this review, we provide a framework for understanding the body of literature that has been devoted to the behavior and reliability of intermittent renewables and discuss recent grid integration analyses within this framework. The modeling approaches required for system characterization are found to depend on the energy penetration of the intermittent technology and recent simulations reveal substantially different behavior in low- and high-penetration regimes. We describe an analytical approach that addresses both penetration regimes and can be used to incorporate the results of grid integration studies into decarbonization strategy analyses.

KEYWORDS | Energy resources; grid integration; intermittency; renewable energy

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I. INTRODUCTION

The purpose of this paper is to provide an overview of the analytical techniques that have been used to determine the ability of intermittent renewables like wind and solar power to supply electricity demand and to highlight emerging areas of research that may improve our understanding of systems with high penetrations of wind and solar. We describe a framework for classifying grid integration analyses that have been conducted over different energy penetrations of intermittent renewables, discuss the modeling considerations that are important for each class of analyses, and present a new analytical method for including the effects of intermittency in developing more realistic decarbonization strategies.

The potential of renewable energy sources to supply a large fraction of electric power demand has been a growing area of research over the last decade, fueled by political climates that increasingly value energy independence, sustainability, and low-carbon and low-air pollution technologies. The necessity of reducing greenhouse gas emissions via the decarbonization of the electricity sector has been demonstrated by the International Panel on Climate Change (IPCC) [1] and has been discussed from an economic perspective in the Stern Report [2]. In this context, resource assessments have noted the potential of renewable technologies like wind and solar power to make significant contributions to decarbonization. McKinsey & Company reported in a study of the carbon abatement potential for several sectors in the United States that wind and solar power could avoid 170 megatons of CO_2 per year by 2030 [3]. Pacala and Socolow notably included 2000 GW each of wind turbines and photovoltaic systems as potential strategies toward stabilizing global greenhouse gas emissions [4]. And in 2001, Jacobson and Masters suggested that the United States could meet its proposed Kyoto Protocol targets by replacing 60% of coal generation with 321–354 GW of wind turbines [5]. Despite the promise of wind and solar power to reduce carbon dioxide emissions, the ability of these intermittent renewable resources to contribute to supplying a fluctuating electricity demand remains an open area of research.

More recently, technical feasibility studies have been devoted to the issue of intermittency in integrating large capacities of wind and solar on to both the Western and Eastern Interconnects in the United States. The Western Wind and Solar Integration Study (WWSIS) described the impacts of intermittency on system operation over the WestConnect area for a portfolio of wind, solar photovoltaic, and concentrating solar power with energy penetrations between 11% and 35% [6]. The report finds that a 35% energy penetration of wind and solar in the WestConnect is feasible, but will require new operational strategies to better utilize existing technologies. The Eastern Wind Integration and Transmission Study (EWITS) performed a similar analysis for the Eastern Interconnect and found that scenarios with penetrations of wind energy up to 30% were feasible if long-distance and high-capacity transmission infrastructure was constructed to improve balancing area cooperation [7]. These reports suggest that relatively short-term renewable portfolio standards can be met with wind and solar power with incremental adjustments to plant operating strategies, transmission and distribution infrastructure, regulatory environments, and electricity markets. These conclusions are supported by the experience in Europe, where some nations have already achieved moderately high penetrations of intermittent renewables. Denmark, which benefits from the flexibility afforded by electricity imports and exports with its European neighbors, produced 18.3% of its domestic electricity supply from wind turbines in 2009 [8].

Despite this progress, there remains an intellectual rift in the literature between the technical feasibility studies that address the limitations of the current electric power system and the resource assessment studies that approach the complete decarbonization of the electricity sector via energy balance analyses. While WWSIS and EWITS indicate that incremental upgrades to the system will enable energy penetrations up to 35%, realizing a completely decarbonized electric power sector will likely require more revolutionary changes to infrastructure, regulations, markets, and perhaps most notably in the context of the "smart grid," communications and controls. The two classes of studies therefore require different assumptions and methodologies and will undoubtedly provide different insights into system behavior. Because the approaches that have been employed in moderate penetration regimes may not be extendable to systems with very high penetrations, care must be taken to place these methodologies into the proper context and to formulate methodologies that can be applied to systems with very high penetrations of intermittent renewables [9].

In the following sections, we discuss the specific modeling considerations that are needed for very high penetration scenarios, focusing on resource variability, resource forecast uncertainty, and resource aggregation effects. We also present a new analytical approach that incorporates the results of both low and high penetration analyses. Finally, we will discuss potential applications of these analyses toward constructing electric power sector decarbonization strategies that incorporate technologies like demand response and energy storage in addition to large-scale renewables.

II. INTERMITTENCY

The difficulty in analyzing electric power systems with renewables like wind and solar lies in accurately characterizing resource intermittency and the ability of the system to accommodate this intermittency. Intermittency in an electric power system is comprised of both variability and uncertainty in the load or the availability of power. Conventional electricity systems exhibit both variability and uncertainty in the supply and the demand: thermal plants introduce variability through unforced outages and uncertainty through forced outages; hydroelectric plants introduce variability due to seasonal changes in precipitation levels, snow melt, and human use; and the load fluctuates with human activity, which is both variable and uncertain. The distinction between conventional systems and intermittent renewables is predominantly in the frequency and magnitude of the variability and in the degree of uncertainty. Fluctuations in the system load are fairly slow due to statistical smoothing and are quite accurately predicted on day-ahead and hour-ahead bases by system operators. Wind and solar power, in contrast, are characterized by more rapid and less predictable fluctuations over time scales from minutes to hours.

The mitigation of intermittency must address both variability and uncertainty. A variable, but predictable resource can be managed with careful day-ahead scheduling, while uncertainty introduces the need for additional reserves that supply the load in the case of unpredictable reductions in generation or increases in load. This same framework can be applied to systems with high penetrations of renewable generation. Milligan explained that with a perfectly accurate wind generation forecast, its variability can be accounted for with day-ahead scheduled units with relatively slow start-up and ramping

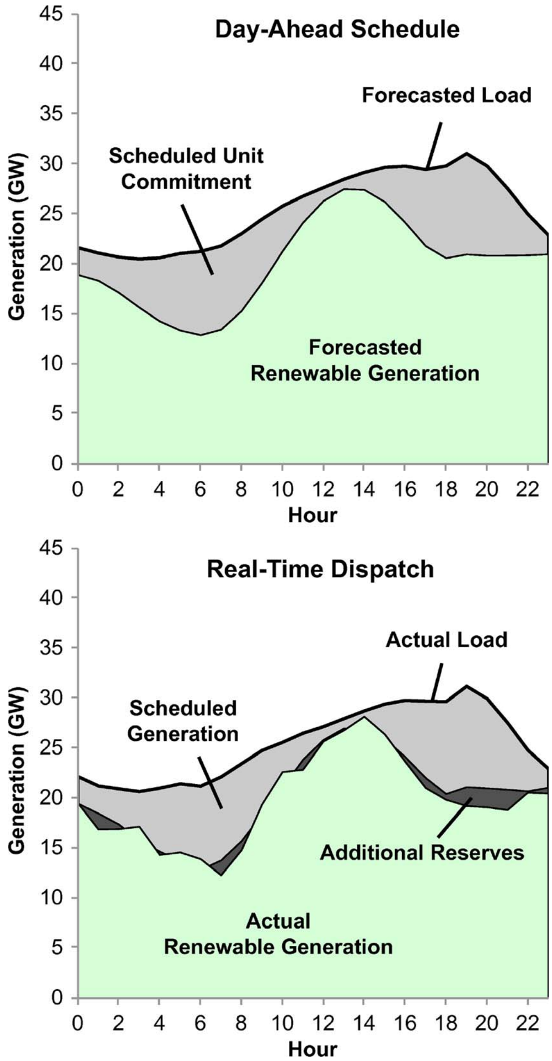

Fig. 1. ***Comparison of possible scheduled generation with the corresponding real-time dispatch. The variability of intermittent generation can be mitigated largely with day-ahead scheduling. Additional reserves are dispatched in real-time to mitigate day-ahead forecast errors. Figure adapted from [11].***

capabilities. The need for additional reserves with low startup costs and high ramp rate limits arises due to the uncertainty in wind generation forecasts [10]. This is illustrated in Fig. 1. Demand response has been proposed as a strategy for reducing these reserve requirements [6], but to date, grid integration studies have largely treated the load as exogenous. An endogenous load, while improving flexibility and efficiency, also introduces added complexity to the system and presents new modeling challenges.

At small scales, when the variability and uncertainty in their power output is within the load-following capability of the existing system, wind and solar power may be treated as load modifiers [12], [13]. However, as the penetration increases, the power fluctuations begin to necessitate additional load balancing and regulation capabilities. The threshold at which the system flexibility must be improved to accommodate wind power intermittency has been estimated by some to fall between 10% and 20% of the total energy generated, while others argue that slight cost increases accompany any positive increase in intermittent penetration [14]. Gross *et al.* have conducted a thorough literature review of the effects of wind intermittency in the British electricity system and have found that while costs are expected to increase due to the balancing and reliability issues introduced by intermittent generation, there is no evidence that reliability of supply will be hurt by wind penetrations up to (and in some studies exceeding) 20% [15].

One advantage of wind and solar facilities is that they tend to be smaller and more distributed than the centralized plants that dominate the present United States electricity sector. Provided the renewable energy plants are robust against network disturbances with appropriate fault ride-through capability, any internal technical failure of a small wind farm has a much smaller impact than a sudden forced outage of a 1 GW nuclear plant, for example. At the time scales relevant to these types of forced outages, the primary concern at high penetrations of renewables is not their variability, but their ability to provide an injection of power in the initial seconds after a forced outage in order to maintain system frequency and tie line flows [16], [17]. Currently, wind and solar systems do not provide frequency support, though this is an active area of research [18], [19], and a facility to provide it is required in some Grid Codes.

A. Intermittency Metrics

The development of metrics has aided in both interpreting system behavior and communicating information to system planners and policymakers. Here we discuss two often-used metrics: the capacity value and cost of intermittency. The capacity value (or capacity credit) of an intermittent generator is the ratio of the capacity of conventional dispatchable plant that can be retired to the capacity of the intermittent generation that is installed in its place to meet the load without compromising reliability. A capacity value can be determined by simulating the system with a given capacity of the intermittent technology of interest while reducing the dispatchable plant capacity until a further reduction would compromise the reliability of the system [20].

The capacity value of wind power has been calculated for a range of systems, using both statistical methods and grid integration models. Values range from 5% to 35% and tend to decrease as the penetration increases [15], [20], [21]. The decrease is attributed to reduced variability and uncertainty associated with aggregation of the resource over larger areas (see Section IV). One disadvantage of approaching the grid integration of intermittent generators with this capacity value paradigm is that it relies on assumptions about the preexisting system. The capacity value is therefore better suited for studying incremental increases in penetration than for designing very high penetration portfolios, which typically utilize greenfield models that remove initial conditions on the composition of the system.

Intermittent renewables can also be characterized by the costs associated with their integration onto the grid. This intermittency cost includes any additional costs associated with real-time balancing of the load and maintaining any additional reserve margin that becomes necessary due to the renewable generators; it does not include the capital cost of the renewable plant or the cost of additional transmission to the plant. The cost of intermittency can be calculated using grid integration models by calculating the cost of electricity with the renewable technology and subtracting the expected cost of electricity were that plant to operate as a dispatchable generator [14]. In Britain, the cost of intermittency for wind power typically falls between 10% and 25% of the direct cost of wind generation, assuming geographically disperse wind farms and penetrations below 20% [15].

While much of the literature on intermittent renewables has been devoted to quantifying the capacity value and cost of intermittency for a given renewable resource, there is little agreement on the precise values of these metrics. This is because both the capacity value and the cost of intermittency are functions of the resource quality, the system load characteristics, the composition of the conventional generator fleet, the strategies employed by and the controls available to the system operator, the electricity market structure, and finally the energy penetration of the technology of interest. The proper use of these metrics is therefore not to make general claims about the ability of intermittent technologies to supply electric loads, but to compare the behavior and reliability of intermittent renewables across different systems, and to identify the types of systems that best incorporate intermittent generation. The more rigorous characterization of these metrics as functions of the energy penetration for a given technology and electricity system remains an open opportunity for research in this field (see Section V).

III. TYPES OF ANALYSES

Several models have been developed to quantify the potential of intermittent renewables to displace conventional generation. In this review, the term "grid integration model" generally refers to a model that treats both the power output from renewables and the electricity demand over time scales of minutes to hours. In addition to time series generation and load data, these models may include transmission constraints, thermal plant operating constraints, reserve requirements, and/or electricity and ancillary service markets. Time steps may range from seconds to hours and simulation periods can be days to years, depending on the purpose of the study. Connolly *et al.* reviewed 37 grid integration models and found that the tools varied widely in objectives and applicability [22].

In the present review, analytical methodologies are classified as zeroth, first, or second order, where zeroth-order analyses provide information about the mean resource quality, first-order analyses address resource variability, and second-order analyses also treat the uncertainties associated with resource variability. Table 1 summarizes the differences between these analyses, which are discussed in more detail in this section. Generally, as the size of the project or the system-wide penetration of renewables increases, the level of information required by the analysis also increases.

A. Zeroth-Order Analyses

Zeroth-order analyses use long-term average measures of resource quality to quantify the resource potential. These analyses can provide simple resource assessments over very large areas, making them especially useful in creating resource atlases or for characterizing the energy density of a region with regard to a specific technology. For wind resource assessments, zeroth-order information typically

Table 1 A Framework for Classifying Grid Integration Analyses of Intermittent Renewables. Analyses Are Classified According to the Level of Information Included in the Analysis, Ranging From Mean Annual Resource Data to Time Series Resource Data With Forecasts and Forecast Uncertainties

Class	Resource Characteristic (s)	Relevant Data	Types of Analyses
0th Order	Resource quality	Annual or seasonal means	Resource atlases Regional power density analysis Small plant siting
1st Order	Resource quality Resource variability	Time series data	Large plant siting Hybrid system planning
2nd Order	Resource quality Resource variability Forecast uncertainty	Time series data Forecasts and uncertainties	Reliability studies Capacity credit determination Intermittency cost analysis Carbon abatement analysis

Table 2 Wind Classes Used for Wind Farm Siting and Regional Resource Assessments [23], [24]. Sites That Are Greater Than or Equal to Class 3 Are Typically Deemed Economically Feasible for Wind Farm Development

Wind Class	Annual Mean Wind Speeds (10m)	Annual Mean Wind Speeds (80m)
1	$v < 4.4$m/s	$v < 5.9$m/s
2	4.4m/s $\leq v <$ 5.1m/s	5.9m/s $\leq v <$ 6.9m/s
3	5.1m/s $\leq v <$ 5.6m/s	6.9m/s $\leq v <$ 7.5m/s
4	5.6m/s $\leq v <$ 6.0m/s	7.5m/s $\leq v <$ 8.1m/s
5	6.0m/s $\leq v <$ 6.4m/s	8.1m/s $\leq v <$ 8.6m/s
6	6.4m/s $\leq v <$ 7.0m/s	8.6m/s $\leq v <$ 9.4m/s
7	$v \geq 7.0$m/s	$v \geq 9.4$m/s

includes the mean annual wind speed at hub height, the corresponding wind class (see Table 2), or the mean annual wind power density. Assuming that the wind speeds follow a Rayleigh distribution, the mean annual wind power density, $\bar{P}$, can be approximated from the mean annual wind speed, $\bar{v}$, and the air density, ρ, using (1) [23]

$$\bar{P} = \frac{3}{\pi}\rho\bar{v}^3. \tag{1}$$

More practically, the quality of the wind resource can be reported in terms of a wind farm's capacity factor, the ratio of the average annual power output from the farm to the rated capacity of the farm. This can be calculated from the power curve of a specific turbine and the wind speed distribution at the site or it can be approximated using (2), which was empirically derived from wind speed data and multiple wind turbine power curves by Masters [23]

$$\text{Capacity Factor} \approx 0.087 \times \bar{v}[\text{m/s}] - \frac{P_{\text{rated}}[\text{kW}]}{(D[m])^2} \tag{2}$$

where P_{rated} is the rated power and D is the rotor diameter of the chosen turbine. Archer and Jacobson produced a global wind resource atlas from a combination of sounding and surface measurements and quantified the global wind power potential by applying (2) to this atlas [24]. They found that the average potential global wind power output at an 80-m hub height over land at high-wind speed ($>$ 6.9 m/s) locations was approximately 72 TW, over five times the approximate annual global energy use in the year of the study. This number has been corroborated from a numerical modeling study by Lu *et al.* [25]. In a similar analysis, Dvorak *et al.* found that development of offshore wind in California could provide approximately 200% of the 2006 electricity demand of the state [26].

Zeroth-order solar resource assessments typically rely on the annual average insolation, a measure of the irradiance integrated over a specified period of time, often expressed as kWh/m^2-day. The insolation can also be conceived of as the equivalent hours per day that a site receives 1-sun (or 1 kW/m^2) of insolation [23]. The annual energy output, E, from a photovoltaic system can therefore be approximated by

$$E = P_{\text{ac}}\ [\text{kW}] \times I\ [\text{h/day of } 1-\text{sun}] \times 365\ [\text{days/yr}] \tag{3}$$

where P_{ac} is the rated power of the photovoltaic system (after inverter and mismatch losses) and I is the annual mean insolation. Turner used zeroth-order information to approximate that 10 000 km^2 of 10%-efficient photovoltaic panels could provide enough energy to meet the annual power demand of the entire United States [27].

While these measures each provide a picture of the energy generation capability of a given site or region, they do not address the variability or uncertainty of the resource. In practical applications, these types of analyses are well-suited to developers of small-scale renewable generation facilities that do not have a significant impact on the intermittency of the system into which they are being integrated. In these applications, a zeroth-order analysis that determines the site that maximizes the average annual energy generation is sufficient to maximize the profits of the wind or solar developer. As the size of the wind or solar farm increases, additional information regarding the temporal variability and uncertainty in the resource may be required in order to better quantify the value of the renewable resource.

B. First-Order Analyses

First-order analyses use additional information to help quantify the resource variability—typically site-specific time series resource data. This level of data is required in order to compare time-synchronized load and resource availability and to conduct load balancing simulations. First-order information has been used to characterize wind speed distributions [28], study the correlations between power output and power demand, and to approximate the emissions associated with load balancing intermittent renewables [29]. These deterministic analyses do not include any information regarding the uncertainty associated with intermittent generation, so they are unable to quantify system reliability.

Nevertheless, deterministic studies have provided useful insights. Maddaloni used a first order power balance analysis of electric power systems the size of Vancouver Island and with generator portfolios similar to those of

Canada, the United States, and the Northwest Power Pool [30]. These simulations demonstrated that power systems that rely more heavily on hydroelectric power, which can be cheaply and quickly ramped up and down to accommodate intermittent generation, have lower operational cost increases associated with increasing wind power penetration. Planning systems with large penetrations of intermittent generators will therefore depend on the characteristics of the electric power system into which they are being integrated.

C. Second-Order Analyses

Additional insights are gained by treating wind and solar forecasts and their associated uncertainties. Large-scale grid integration of wind and solar power will inevitably require the use of short-term forecasting tools for both day-ahead unit commitment and hour-by-hour grid operation. Giebel sets the threshold at which these forecasting tools become necessary at 5%–10% penetration for wind power [31]. Second order analyses, which include information regarding the uncertainty in the availability of intermittent resources, have shown that forecast accuracy can have a significant impact on the design and operation of systems with large-scale intermittent generators.

Watson used numerical weather prediction models and the National Grid Model (a power scheduling model for the England and Wales National Grid) to show that wind speed forecasts could be used to achieve both system-wide cost and fuel savings for wind power penetrations above 15% in the 47 GW-peak demand system [32]. Barthelmie *et al.* characterized potential forecasting methods using observed systematic bias and random errors from actual forecasting methods and found that the value added to wind power from forecasting depends strongly on the accuracy and cost of the forecast, but that forecasting was generally beneficial for wind farms larger than 100 MW [33].

A consideration of load and meteorological forecasts as well as their associated uncertainties is necessary for grid integration models that seek to comment on grid reliability. Second order analyses are therefore of interest to any utility or independent system operator that seeks to reliably meet demand with a high penetration of intermittent generators. From a system modeling perspective, second order analyses are also required into order to produce accurate approximations of the capacity value and the cost of intermittency. These analyses are typically carried out using a grid integration model that accounts for the stochasticity of intermittent resources via Monte Carlo simulation and/or stochastic optimization.

The WILMAR model formulates the grid operation problem with high wind power penetrations as a stochastic linear program [34], [35]. The model solves the least-cost dispatch problem while considering the various power and ancillary service markets in the Nordic countries. Wind power forecast errors are accounted for by producing a number of potential wind power forecasts using a Monte Carlo simulation. The WILMAR model has been used to show that wind power reduces the operational costs associated with electricity generation (neglecting capital costs) in the region containing Germany, Denmark, Finland, Norway, and Sweden. The simulations also showed the marginal revenues earned by wind farms are expected to decrease with increasing penetrations due largely to an increase in the penalties associated with forecast errors. Makarov *et al.* have built a similar Monte Carlo simulation to represent fluctuations in load and wind power output while also modeling the scheduling, real-time dispatch, and regulation processes experienced by the California ISO (CAISO) in order to determine the regulation and load capability required to manage 6700 MW of wind on the CAISO system (with a peak demand of 50 GW) [36]. Their work showed that while regulation and load following ramp rates increased to handle the variability and uncertainty in wind power output, the increases were still within the ramping limits of the existing system.

The continued use of Monte Carlo methods to investigate the effects of large-scale intermittent generation on system operation will require improved statistical treatments of forecast uncertainties and methods for scenario production. Because of the importance of system reliability, system planning is constrained largely by extreme events. Accurate simulation of these events will require improved characterization of forecast error distribution tails. Furthermore, resource forecast errors are comprised of both errors in magnitude (e.g., the wind speed associated with an incoming weather front) and errors in phase (the timing of the front's arrival), but phase errors are typically not treated explicitly in scenario production for Monte Carlo grid integration analyses. This presents an opportunity for the application of new autoregressive, Markov, and/or artificial neural network models to more accurately represent the magnitude and phase of forecast errors [37]–[40]. These methods can be used to produce more realistic wind power realizations for intermittency analyses and for analyzing the benefit of new stochastic unit commitment methods [41], [42]. New statistical methods may also improve short-term forecasting in real systems.

IV. AGGREGATION EFFECTS

For systems with large penetrations of intermittent renewables, the temporal variability and uncertainty described in the previous section will also depend on the correlations between power output at different sites and from different resources. Several studies have shown that aggregation of multiple intermittent generators can reduce the variability and the uncertainty of a portfolio, either from statistical smoothing of a single technology employed over large geographical areas or from combining technologies that utilize different (and often uncorrelated) renewable resources.

A. Geographical Aggregation

Correlation is a measure of how two data sets linearly co-vary and can be used to understand wind farm power output [43]. Aggregating the power output of negatively or low correlated renewable generators reduces intermittency. As the distance between two renewable generators increases, the correlation in power output between them generally decreases. This correlation is a function of the resource, distance, terrain, and time scale. These correlations between distant generators serve as metrics for the geographic aggregation effect and have been extensively studied for wind power. Kahn studied the correlations between wind speeds at six sites throughout California and found that in general, the correlation coefficients decrease with increasing distance between sites [44]. At short distances within wind farms, several authors have found low correlations between wind turbines at time scales less than 1 min, but high correlations beyond 1 min [45]. The low correlations at short distances and short time scales is attributed to turbulence and terrain effects. This effect can be modeled to aggregate the power output of wind turbines in a wind farm using a multi-turbine power curve for system studies [46], [47].

The correlation of power output between distant wind farms and the benefits of aggregation have been investigated in Europe [48]–[51], Japan [52], and the US [28], [53]–[55]. Hourly correlations between wind farms decrease rapidly at 100 km and generally remain low, but slightly positive, for distances up to 1000 km. This has been shown by Wan in the United States [53] and Sinden in the United Kingdom [51]. The low correlations are attributed to the length and time scales of weather systems. At distances greater than about 1500 km, wind farms can be negatively correlated as 1500 km is roughly associated with the scale of pressure systems [49]. Representative correlations, distances, time scales and their impact on grid integration were compiled from several of the previously noted studies and are shown in Table 3.

Table 3 Summary of the Statistical Observations and Effects for Geographic Diversity of Wind Power. The Benefit of Geographic Diversity Is Dependent on the Distance and Time Scale of Interest. Geographically Diverse Wind Benefits the Electric Power System Depending on the Relevant Time Scale. Correlations Vary Widely Between 100 km and 1000 km Depending on Terrain and Orientation of Sites Relative to the Movement of Weather Systems

Distance (km)	Correlation (1 hr avg)	Time scale of benefit	Electric power system benefits
1	0.9	seconds-minutes	Voltage control
10	0.9	minutes-10 minutes	Regulation
100	0.7	1 hr	Regulation Operating reserves
500	0.35-0.7	hours	Operating reserves Forecasting Scheduling
1,000	0.1-0.5	hours	Operating reserves Forecasting Scheduling
2,000	0	days	Forecasting Scheduling Reliability
10,000	-0.1	days-weeks	Reliability

The effects of aggregating photovoltaic systems over large areas has also been investigated over various temporal and geographical scales [56]–[59]. These analyses differ from wind analyses because the solar resource fluctuates due to two different phenomena: deterministic fluctuations in the "clear-sky" insolation that depend on the location of the sun in the sky; and stochastic fluctuations that arise due to cloud cover. The deterministic fluctuations are highly correlated between sites that have similar latitudes and longitudes, so the benefits of geographic aggregation arise predominantly from the stochastic fluctuations in cloud cover. Mills used measured data at multiple sites across the Southern Great Plains to show that the subhourly variability of the solar resource only slightly exceeds that of the wind resource over a similar network [58].

The same types of grid integration models that use first or second order information can also incorporate aggregation effects by including multiple intermittent generator sites. DeCarolis and Keith modeled a system that incorporated five geographically disperse wind farms across the United States with both single-cycle and combined-cycle gas turbines and compressed air energy storage facilities to achieve load balancing over a five-ear period at hour intervals [60]. The study found that increasing the number of geographically dispersed wind farms in the system decreased the levelized cost of electricity, despite the added transmission costs. Denholm and Margolis have presented one of the few grid integration studies focused on large-scale solar power [61]. They modeled power output from 9 sites throughout ERCOT with first order data and characterized the limits of the pre-existing system in terms of the minimum loading of the system: the total power that must be generated by inflexible conventional plants at a given time. Their analysis determined that the minimum loading problem could typically be avoided when PV installed capacities remained below 20% of the system peak demand for systems like ERCOT (with a peak demand of approximately 60 GW).

Geographical aggregation has also been found to reduce forecast errors associated with portfolios of intermittent generators. Focken *et al.* used historical forecast data from wind farms in Germany to show that the forecast error can be significantly reduced by considering ensembles of wind farms, rather than single sites [62]. They found that the reduction in forecast error depended more on the spatial extent of the ensemble than the number of wind farms in the ensemble. Similar conclusions have been reached by Boone with data from wind farms in Denmark [63] and Lorenz *et al.* in a study of photovoltaic power output forecasts over large geographical areas [64].

The benefits of geographical aggregation can be realized both by system operators and power producers. System operators will benefit from expanded transmission infrastructure to connect distant resources and from improved cooperation between balancing areas [6]. Similarly, power producers can reduce the risk associated with their portfolios by owning assets throughout large geographical areas and operating those facilities as single entities, or "virtual" power plants. From a modeling perspective, the effects of geographical aggregation must be accounted for by both including multiple sites in intermittency analyses and properly treating the correlations between these sites, particularly in Monte Carlo simulations that rely on statistically generated time-series resource data.

B. Combining Multiple Technologies

The aggregation of power from a diversity of renewable resources also reduces intermittency even when the resources are colocated. Renewable power generated by solar radiation and atmospheric dynamics like solar, wind, and wave power often have low cross correlations because of the time scales of the underlying physics. Tidal power operates on diurnal or semidiurnal cycles of the lunar day depending on the location, which is uncorrelated over yearly time scales to both electricity demand and the other renewables. Similarly, small hydropower, river current, and ocean current renewables have strong seasonal variations but rarely any significant diurnal correlation to solar or wind power output. The effects of renewable resource aggregation on facilitating their grid integration has been extensively studied both with analyses of specific resources and with system-wide generation portfolio optimization models. Specific correlations between resources and electric load have been studied for wind and solar [65]–[69] and wind and wave [70], [71].

Energy system models have also been used to implicitly investigate these synergies by analyzing portfolios of intermittent generators. Lund has developed a deterministic energy system model (EnergyPLAN) that combines hour-by-hour power balance simulations with electricity market simulations and an economic model capable of producing socio-economic feasibility studies [72]–[75]. The model has been used in a wide range of applications, including an analysis of the potential of meeting 100% of the energy demands of Denmark in the year 2050 with renewable energy systems [74]. These total energy system models (which also treat transportation, heating/cooling, and other energy intensive nonelectrical sectors and processes) can provide more comprehensive energy sector carbon abatement analyses [76], [77].

Hart and Jacobson applied a stochastic approach to analyzing the potential of various renewable portfolios to contribute to supplying the CAISO demand and reducing the carbon emissions associated with supplying this demand [11]. The Monte Carlo simulations suggested that despite very large reserve requirements to maintain system reliability, a 99% (by energy) carbon-free generating portfolio consisting of wind farms, concentrating solar thermal plants, distributed photovoltaics, hydroelectric plants, and baseload geothermal plants could reduce carbon dioxide emissions by at least 80% when compared to the least cost portfolio for the years 2005 and 2006.

V. NEW SYSTEM CHARACTERIZATION METHODS

Application of these modeling methods to real electric power systems can yield a significant amount of information, including the metrics discussed in Section II. While point values are typically reported for the capacity value and cost of intermittency, analyses that treat these metrics as functions of the penetration of intermittent renewables will aid further understanding. The reserve capacity required to meet reliability standards can also be reported as a function of renewable energy penetration in order to better characterize the systems.

One additional method of characterizing the ability of intermittent renewables to supply a fluctuating electric power demand is to build a function describing the relationship between the installed capacity of the intermittent portfolio and the annual energy generation from the portfolio. This generation function will depend on the resource availability and predictability, the energy conversion technology and its associated controls, and the system into which it is being integrated. An example generation function for wind power has been produced using the model described in [11] with data from the CAISO operating area over 2005–2006 and is shown in Fig. 2.

A. Penetration Regimes

The generation curve in Fig. 2 can be broken into two regimes: a "linear regime," in which the generation scales linearly with the installed capacity with a slope proportional to the expected capacity factor of the technology; and a "curtailment regime," in which the generation function exhibits negative deviations from its low-capacity trajectory as generation is shed in hours when it would otherwise exceed demand. In the curtailment regime, as capacity increases, the annual generation approaches a maximum value, which depends on the nature of the electric power system into which the technology is being integrated (more specifically it depends on the system-wide demand and the must-run generation on the system).

In general, zeroth-order analyses assume a linear generation function, with a slope proportional to the capacity factor of the technology, while first and second-order analyses reveal nonlinearities in the curtailment regime of the generation curve. Generation curves produced by first- and second-order models can be approximated by the following equation for the generation, G, from a given renewable technology or portfolio as a function of its installed capacity, C:

$$G(C) = \begin{cases} kC, & C < C_q \\ G_\infty(1 - e^{-\gamma C}), & C \geq C_q \end{cases} \tag{4}$$

where k is the equivalent number of hours per year that the generator runs at maximum capacity, or 8760 hours times the expected capacity factor; C_q is the curtailment point, the minimum capacity at which curtailment is required in order to exactly meet demand; G_∞ is the maximum generation that can be integrated into the system from the generating technology of interest (neglecting renewable capacity constraints); and γ describes how rapidly the generation approaches G_∞ in the curtailment regime. To a first approximation, the generation function for an intermittent technology in a specified electric power system can be uniquely characterized by k, C_q, and G_∞. Note that the curtailment regime is only relevant for technologies that include curtailment controls. Rooftop photovoltaics, the generation from which is currently not curtailed, are expected to have linear generation curves that end at the curtailment point.

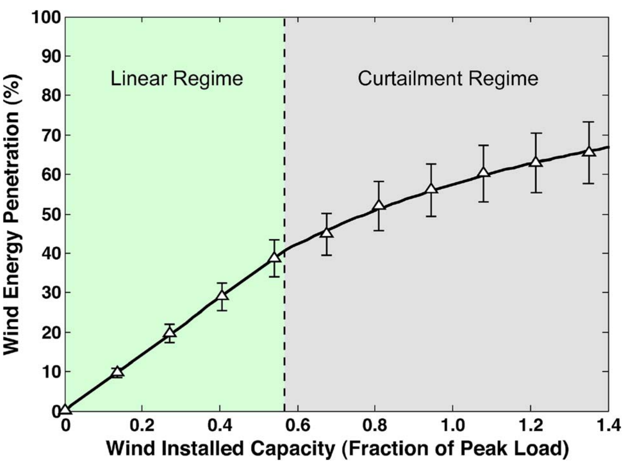

Fig. 2. ***Generation curve for wind power integration into the 2005–2006 CAISO operating area using the grid integration model in [11] with a conventional fleet consisting of hydroelectric and natural gas turbines and an updated dynamic reserve scheduling module. The triangles represent simulation results and the line shows a fit of the data to the function in Equation (4), with $k = 3360$ h, $C_q = 30.9$ GW, and $G_\infty = 208\,000$ GWh. Error bars are equal to 12% of the generation from wind, which was the largest deviation of a realization from the mean in the highest penetration simulation. Each data point required approximately 10 h of computing time on a 2.2 GHz Intel Core 2 Duo processor with 2 GB of RAM.***

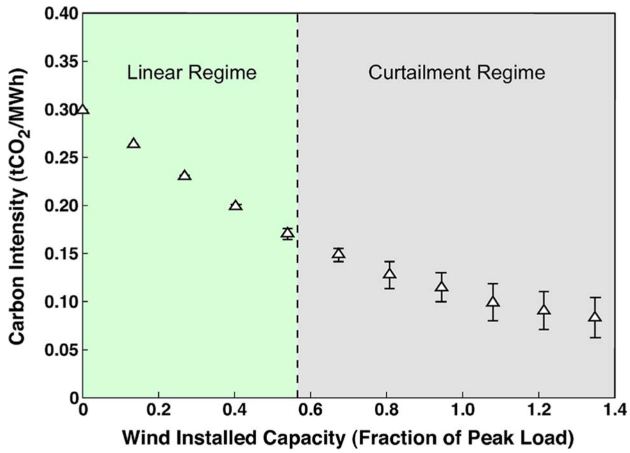

Fig. 3. ***Carbon curve for wind power integration into the 2005–2006 CAISO operating area using the grid integration model in [11] with a conventional fleet consisting of hydroelectric and natural gas turbines and an updated dynamic reserve scheduling module. Error bars are equal to the largest deviation of a realization from the mean.***

Grid integration models can also be used to build carbon curves for intermittent renewables, where the system-wide carbon intensity (in tCO_2/MWh of system-wide generation) is plotted as a function of the installed capacity of the renewable technology. This is shown for wind power in the 2005–2006 CAISO example in Fig. 3. The carbon abatement potential of a given technology can be reported using these curves, but care must be taken to note the composition of the conventional generation fleet into which the renewables are being integrated. The carbon curve for wind power in a system dominated by hydroelectric power will, for example, differ considerably from the carbon curves associated with systems that rely heavily on natural gas or coal generation.

B. Analytical Applications

One major goal of improving the characterization of intermittency with grid integration models is to provide a better means of treating intermittency in energy planning tools that are capable of building decarbonization strategies and analyzing the effects of specific policies on the composition of the electricity sector. The difficulty in including intermittency in long-term planning studies lies in resolving the short-term phenomena that arise in the grid integration studies discussed in this review with planning tools that typically have time steps of years. The generation and carbon curves shown in Section V provide a means of incorporating the results of higher resolution grid integration analyses into these longer term analyses.

The concavity of the generation function in Fig. 2 lends itself well to optimization-based planning models that include constraints on the minimum energy penetration of renewables. Generation functions may therefore be especially useful for characterizing potential paths towards meeting statewide Renewable Portfolio Standards (RPS) or a national Renewable Electricity Standard (RES). As a simple example, if one wishes to find the least-cost trajectory (based on projected electricity demand and cost functions) toward meeting an RPS of 50% in year T with a renewable technology or portfolio that can be described by (4), then the RPS will be met when the following two constraints are included in the planning optimization problem, in addition to the usual renewable capacity constraints:

$$-kC(T) \leq -0.50 \times G_{TOT}(T) \quad (5)$$

$$G_\infty \left(e^{-\gamma C(T)} - 1\right) \leq -0.50 \times G_{TOT}(T) \quad (6)$$

where $G_{TOT}(T)$ is the projected total system-wide energy generation over year T. In (5) and (6), the only optimization variable is the installed renewable capacity, $C(T)$. The parameters G_∞ and γ likely change over time with the changing electricity demand, but do not depend on $C(T)$.

An improved understanding of how the parameters in (4) depend on easily accessible information, like peak demand, annual energy demand, and must-run capacity may enable approximate constraints of the form in (5) and (6), bypassing the time-intensive simulations required to produce the generation and carbon curves. Approximations of these curves may also lead to new "rules of thumb" in planning renewable energy buildout scenarios and designing policy initiatives that incentivize efficient renewable portfolios.

The carbon curve shown in Fig. 3 also has the correct convexity for cost minimization problems that include carbon cost terms or that constrain the maximum allowable carbon emissions. The inclusion of these curves as cost terms and/or constraint functions in energy planning optimization problems may therefore improve our understanding of the effects of carbon taxes and cap-and-trade policies toward meeting electricity sector decarbonization targets.

In addition to policy implications, generation and carbon curves may also help to inform future technological development. Grid integration models can be updated to include new technological advances, including but not limited to demand response, energy storage, efficiency improvements, and capacity factor improvements for intermittent technologies. The generation and carbon curves (as well as the intermittency costs, capacity values, and/or reserve requirements) resulting from these simulations will provide standard metrics with which to judge the utility of these new strategies towards improving overall system efficiency, maintaining reliability, meeting an RPS, or reducing carbon dioxide emissions.

VI. CONCLUSION

While zeroth- and first-order analyses, which focus on mean resource quality and resource variability, respectively, provide useful insights into the resource potential and behavior of intermittent renewables, second-order analyses, which also address the stochastic nature of intermittent renewables, are needed in order to accurately represent the effects of grid integration on system operation and reliability. Depending on the application, these effects have been characterized by the capacity value or the cost of intermittency, metrics that depend strongly on the generating technology, the system into which that technology is being integrated, and the penetration of the technology. Because of these dependencies, specific values for these metrics that have been determined by low- to moderate-penetration grid integration analyses cannot be directly extended to very high penetration scenarios, which may utilize updated conventional generator fleets and new operational strategies.

The characterization of systems that can achieve very high penetrations of renewables and include new technologies like demand response and energy storage therefore relies on the development of new grid integration models. As is discussed in this review, these models must include time series meteorological and load data, statistical treatments of meteorological and load forecast errors, and an analysis of system reliability. Studies on the effects of intermittency within electric power grids must also account for the effects of aggregation over the geographical area of interest on the time scales of interest, as failing to include multiple sites within an operating area will tend to overestimate the variability and underestimate the predictability of the aggregated resource.

For incorporation into long-term energy planning analyses that inform policy decisions, intermittent technologies and renewable portfolios can be characterized within specific systems by their associated generation functions and carbon curves. When combined with cost projections, these curves can be used within larger energy models to characterize potential trajectories toward a decarbonized electric power sector and to help identify policy initiatives that incentivize these trajectories. The results of these studies will also inform efforts directed toward reducing technological and institutional barriers to high penetration grid integration of renewables, including transmission infrastructure planning, the development of new interconnection regulations and protocols, and the development of new communications and controls that simultaneously support system reliability and increasing penetrations of renewable energy technologies. ■

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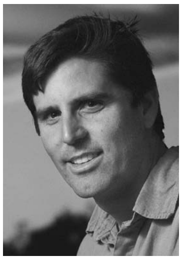

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