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Spatial and temporal analysis of electric wind generation intermittency and dynamics

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ABSTRACT

A spatial and temporal analysis of wind power generation characteristics was conducted in order to determine the implications of intermittent wind generation dynamics on the profile of the electric loads that must be balanced by dispatchable electrical generators on the electric grid. A parametric analysis was conducted to evaluate the sensitivity of the typical magnitudes of wind power fluctuations on different timescales, power variation range, typical daily and seasonal wind profiles to wind farm size and regional distribution. A methodology to evaluate wind dynamics based on power spectral density analyses have been developed. Results indicate that increasing the size of a local wind farm significantly reduced the magnitude of wind power fluctuations on timescales faster than 12 h, with the largest reductions occurring at the fastest timescales. Additional reductions in power fluctuations can be achieved with the implementation of local and regional distribution of wind turbines in disperse high wind areas. In these cases, it was discovered that the timescale band within which the largest reductions in power fluctuations occurred was dependent on regional geographic features, and did not necessarily correspond to the fastest timescales. In addition, it was also discovered that the aggregation of wind power from different regions could produce a more uniform frequency distribution of power fluctuation reductions.

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1. Introduction

Due to increasing concerns regarding national security, climate change, and environmental impacts of the current energy infrastructure, renewable power generation systems are receiving increased attention. Over the past few years, wind power has emerged as the fastest growing sector of the U.S. renewable energy market [1–3], contributing 42% of all new electricity generation capacity in the year 2008 [4]. Cumulative installed wind capacity has grown from about 3000 MW in the year 2000 to just below 12,000 MW in 2006 [5]. In addition, 40,400 MW of new peak wind capacity is expected to be added by the year 2012 [4], with forecasts of reaching a total capacity of 300 GW by the year 2030 [4]. This level of continued growth is due to many factors, including but not limited to: (1) the sustained renewal of production tax credits to subsidize new wind projects, (2) an increased focus on utilizing U.S. energy resources that have zero or near-zero carbon emissions, (3) the high amount of currently unused high wind resources in the U.S., and (4) the relatively low price of wind turbine projects compared to other renewable power projects of similar scale.

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Wind power exhibits a number of favorable characteristics as an emerging renewable energy resource. The leveled cost of electricity generated by wind has continually decreased due to improvements in wind turbine technologies, and is projected to undercut the price of electricity generated from coal by 2020 without subsidies [6]. With the presence of subsidies, changes in market conditions, and mitigation of current engineering challenges associated with wind turbines as outlined by Dalili in [7], it is possible that wind power may become cost competitive at an earlier date. In addition, the development of wind turbine technology does not require a large amount of advanced or exotic materials. Large wind turbines require balsa wood, steel, fiberglass, carbon fiber, permanent magnets, and copper [5]. Although large growth in wind power is expected to bring about a large increase in the required material use and manufacturing capabilities, these issues have not been determined to be limiting factors in reaching high levels of wind penetration [8].

As electrical wind generation continues to increase in many electrical power systems around the world, wind intermittency characteristics are becoming increasingly significant. Compared to natural gas-fired turbine generators or hydroelectric power generation, wind power is not as easily dispatched. The electrical power output from wind turbines is limited by instantaneous wind

availability, with only a few minutes of electric power stored within the turbine rotational inertia. Dispatchable electric generation must balance the difference between the electric load and wind generation. To maintain electric grid reliability, variation in both electric loads and wind power generation must be compensated for by dispatchable energy resources on the grid. The purpose of the presented research is to assess key characteristics associated with wind power generation with sensitivity to wind farm size and varying degrees of regional dispersion, which inherently have implications for supplementary dispatchable power generation.

2. Background

The character of wind power intermittency is a subject which has garnered much interest from many academic and government research groups. Due to the rapid growth of wind power which has taken place in recent years, analyzing and understanding the character of wind power fluctuations has become an area of high importance.

Wan [9] outlined a report which analyzes the characteristics of wind power fluctuations on different timescales. Utilizing data from 4 sites in Texas, one in Iowa, and one in Minnesota at a 1 s resolution, this study analyzed wind characteristics at the 1 s, 1 min and 1 h timescales. It was established that the use of a single wind turbine to characterize the behavior of a wind farm or fleet of wind farms is erroneous, since single wind turbines exhibit increased variability compared to that of an entire wind farm. Wind power variations on hourly timescales were found to be much larger than the sub-hourly variations, reaching up to 70% of the entire rated capacity of the wind farm fleet, although it was discovered that such events were very infrequent.

Holtinen [10] conducted an analysis of wind power variations in the Nordic countries utilizing data with a 1 h resolution. The statistics of wind power vectors representing different levels of geographic aggregation were used to assess the effect of geographic aggregation on wind power dynamics. It was found that geographic aggregation reduced the occurrences of near-zero wind power output and near peak wind power output for the entire wind farm fleet as a probabilistic effect. The correlation between the power output of wind turbines at different separation distances was also examined to explain the effect of decreasing variability with geographic aggregation. The power output of wind farms spaced less than 100 km apart were found to be highly correlated and farms spaced more than 200 km apart were found to only be weakly correlated. In general, the value of the correlation coefficient between sites as a function of separation distance tended to follow an inverse exponential trend.

In another study, Holtinen [11] conducted a study focusing on design elements of the electric power system required to accommodate large amounts of wind power. A section on wind power variability highlights that such variability decreases as more turbines are added to the aggregate profile and wind power plants are distributed over a wider area. The magnitude of wind power variability decreases as the timescale decreases, and the largest changes in power occur over long timescales (1 h or longer). The hourly variations in wind power did not smooth out to any large extent within a single wind farm.

A study presented by Apt [12] utilized a spectral method for analyzing wind power variability. Utilizing hourly data from 104 sites for a 3 year timeframe and 1 s data for a 10 day period, the power spectral density (PSD) of the wind profiles were calculated using a periodogram to examine the frequency content of the signals. It was found that the high frequencies contained considerable power in the PSD.

In addition, a number of other studies have been carried out with similar scopes, coming to very similar conclusions regarding

the character of wind power fluctuations and the effect of geographic aggregation on such character [13–16].

While there have been a multitude of efforts that have provided insights into the character of wind power intermittencies, these studies generally limited their analyses to specifically defined timescales determined by the resolution of the data. There have not been many studies that characterize wind power intermittency and conduct sensitivities on the severity of these intermittencies on a continuous spectrum of timescales. This study utilizes spectral methods to examine and compare the severity of fluctuations in wind power on different timescales simultaneously, as the timescale of power fluctuation is a key design factor that determines the appropriate energy management strategy that must be implemented on the grid to compensate for such variations.

3. Analysis of wind characteristics

The presented research uses Southern California as a basis of the analysis. Southern California has a number of significant wind resource areas which have been determined to exhibit high wind capacity potential [17]. Areas that are suitable for utility scale use are numerous throughout the region [18], and California state policies are in place to reduce greenhouse gases [19] and achieve a 33% renewable penetration level by 2020 [20], making use of the state's wind resources essential.

3.1. Wind data and verification

The specific wind power data set used in this study has been obtained from the NREL Western Wind and Solar Integration Project (NREL-WWSI) [17]. The data provides 10 min temporal wind speed and electrical power output at a 2 km by 2 km spatial resolution for potential wind sites across the United States for the years of 2004 through 2006. Each 4 square kilometer area of the study is assumed to contain ten 3 MW wind turbines. Details of the data set compilation are available in the report presented by the 3TIER Corporation [21]. The data set was composed using a meso-scale model developed by 3TIER Corporation. The performance curve for the Vestas V90 3.0 MW turbine was used to determine the wind power output potential of each block.

The NREL database organization is presented in Fig. 1. Each wind turbine icon or colored dot on the map is representative of one 4 square kilometer block. The icon colors represent the effective capacity factor of each block at a height of 100 m as shown in Table 1.

For the current study, the wind farm site in the Tehachapi, California region is examined due to its high wind potential [18], regional proximity to major population centers in the Southern California region, as well as its potential to support a large capacity of wind power generation.

Data from the NREL model was obtained and uploaded into an SQL data server, where it was extracted by applying SQL database queries. One example of such a query was used to effectively calculate the sum of the power output from every turbine block confined to a user-specified set of spatial coordinates (latitude and longitude). Wind power data was also obtained for different geographical regions, allowing the evaluation of wind power characteristics as a function of regional dispersion. This approach to wind power data is important since point-based measurements from weather stations do not account for the inertia of the wind turbine farm or spatial effects, and will predict a significantly higher degree of power dynamics than would actually be experienced from a wind farm.

Wind power results from this model were verified against wind power production data from the currently installed Tehachapi wind

Fig. 1. NREL wind farm potential map in the Tehachapi region of Southern California.

farm as shown in Fig. 2. Data was provided by Southern California Edison [22] for the month of April 2005 as presented by the solid lines in Fig. 2. The modeled wind profile which encompasses the currently installed wind farm is dubbed the “Tehachapi installed model”, and is based upon the known areas of wind turbine installations and estimates of wind turbine sizes and dispersion in this region as coupled to the NREL wind data [17]. Model results are presented as dashed lines for the representative days (Fig. 2a) and average diurnal profiles (Fig. 2b). The Tehachapi installed model well represents the daily production from April, 2005 (Fig. 2a) and the average diurnal profile [23] for the month of July 2005 (Fig. 2b). In addition, the current analyses considered the entire Tehachapi area wind resource as represented by the “Tehachapi Farm Model” curve, and shown for comparison in Fig. 2b.

The Tehachapi installed model well simulates the average measured power production profiles, sharing the same qualitative characteristics and shape. However, the predicted average diurnal profile has higher capacity factors during the peak hours and lower instantaneous capacity factors during the daytime hours than the SCE data. This trend is displayed to a reduced extent for the July 2005 results of Fig. 2b. This discrepancy is most likely due to differences between the wind turbine units assumed in the model and the actual wind turbine units currently used in the Tehachapi

region. The model determines power output using the power curve of the Vestas V90 3.0 MW turbine, which is larger than most of the installed units. The currently installed units exhibit significant variation due to the diversity of wind turbine units from various manufacturers. The various cut-in speeds of the installed turbines compared to the single, higher cut-in speed of the Vestas turbine lead to the more dynamic model responses to wind speed (especially for low wind velocity) compared to the data of Fig. 2a. The rated speed of the Vestas turbine is about 15 m/s, which is generally higher than that of the installed turbines allowing modeled power to take advantage of the higher wind speeds at night, explaining the higher nighttime capacity factor of the model.

The model is also not expected to exactly predict the data due to other factors not considered in the model such as the diversity in the technology level of the currently installed wind turbines and wider variations in hub height (100 m in the model versus 60–100m in the data). Nonetheless, Fig. 2 presents comparisons of wind power measured and predicted for two days in the year 2005, April 5 and April 9 that adequately verify and capture essential intermittencies, day-to-day variability, and dynamics and ramp-rate features of wind power for this region. It is important to emphasize that strategies to address wind power intermittency must be based upon data for the individual hours and days, not the average wind power profiles, since as can be seen from Fig. 2a, average profiles do not capture the intrinsic daily wind variations and “random” wind behavior.

Table 1

Legend for NREL wind potential map capacity factors.

Icon color	Wind potential capacity factor
Blue	<25%
Green	25–30%
Yellow	30–35%
Orange	35–40%
Red	>40%

3.2. Wind farm characterization

The characterization of the severity of wind power fluctuations is not trivial. Over a given year, the power output of a wind turbine farm of any spatial scale spans the entire range of power production

Fig. 2. Current wind power model verification with Tehachapi wind farm power data: (a) April 2005, (b) July 2005.

points from zero output to rated capacity, therefore the absolute range of wind power variation does not provide much information about the character of wind power fluctuations. Power fluctuations tend to occur across a range of timescales. Therefore, to quantify the intermittency exhibited by wind farms of different spatial scales, a proper metric must be used that takes into account the timescale distribution of wind turbine power fluctuations.

To evaluate this aspect in more detail, a power spectral density distribution of each wind farm representation is used. The power spectral density represents the respective weighing and significance of the frequency of wind power variations with respect to a given reference signal. Each signal was normalized by its maximum value, and the power spectrum of each normalized signal is determined to produce a frequency distribution of spectral signal power, with units of watts per hertz (W/Hz). Note that spectral power is an artificial quantity that arises from the magnitudes of the Fourier series expansion of the signal, and is not the same as the physical wind power. Spectral power is related to the average amplitude of the fluctuations of a signal at a given frequency, which in this case refers to the average physical wind power fluctuations. In order to compare the power spectra of the different wind power signals, one of the signals is chosen as a reference, and the spectral power of the other signals at all sample frequencies are compared to it via normalization to obtain the power spectral density in units of

decibels (dB). Since spectral power is proportional to the square of the amplitude of a signal, the decibel representation is related to the ratio of signal amplitudes by:

$$L_{dB} = 10 \log_{10} \left(\frac{P_1}{P_0} \right) = 10 \log_{10} \left(\frac{kA_1^2}{kA_0^2} \right) \quad (1)$$

$$10^{\frac{L_{dB}}{10}} = \frac{P_1}{P_0} = \frac{A_1^2}{A_0^2} \quad (2)$$

Where P_1 is the spectral power of the signal of interest and P_0 is the spectral power of the reference signal, as computed by the power spectral density algorithm, and L_{dB} is the decibel value. A is the average amplitude of each signal respectively, which in this case corresponds to the average magnitude of physical wind power fluctuations at that frequency.

This approach allows quantification of the relative increases or decreases in the magnitude of power fluctuations with respect to the reference signal. For example, a positive dB value at a particular frequency indicates that the power spectra of a particular signal displays larger average power fluctuations than the reference, while a negative dB value indicates the opposite. Note that due to the logarithmic nature of the decibel scale, positive and negative dB values correspond to different scaling. For each of the power spectral density estimates displayed herein, the reference signal will be stated.

It is important to note that a PSD quantifies the average power weighing of the frequency and does not quantify the absolute variations or peak transient characteristics that can be expected at that timescale. In terms of wind power, the PSD helps quantify the typical wind power variation at a given timescale. Average power fluctuations are essential to evaluate since these variations dictate the typical level of dynamics that supporting generators can expect. However, the PSD does not quantify the peak ramp-rate capability required by balancing generators on the grid. Nonetheless, the power spectral density is found to be a very insightful tool for characterizing wind farm representations. Here a modified covariance algorithm in MATLAB was implemented for this analysis.

The timescale of the variations is displayed in micro-hertz with important timescales corresponding to given frequencies as shown in Table 2.

3.3. Effects of wind farm size on generation dynamics

The sensitivity of wind farm power generation dynamics to wind farm size on a land area basis is presented herein. Five different wind farm sizes were chosen, each corresponding to areas encompassing different numbers of wind turbine blocks. These farm sizes and their location are presented in Fig. 1. The section of the potential map representing the currently installed wind farm in

Table 2
Frequency to timescale conversion.

Timescale of variation (hr)	Frequency (μ Hz)
Month (720)	0.386
Week (169)	1.64
Full day (24)	11.5
Half-day (12)	23
Quarter-day (6)	46
Three-Hour (3)	92
Hourly (1)	275
Half-Hour (0.5)	550
20 min (0.33)	833

Tehachapi is taken to be the smallest size, and the “Small”, “Medium”, and “Large” farm representations are taken to be expansions of that wind farm to increased fractions of the potential map, where the “Entire Farm” representation encompasses the entire potential map of Fig. 1. Since the magnitude of the power generated from each wind farm representation varies widely, the absolute wind farm power profiles have been normalized by their respective maximum values. Afterward, each profile is scaled to a nameplate capacity of 30 MW for comparison.

The magnitude of power variation at various timescales is determined by applying a PSD estimation for each wind farm representation and choosing the reference signal to be the power spectrum of the currently installed wind farm, as shown in Fig. 3. Due to the resolution of the wind power data (10 min), the PSD can only be calculated up to a frequency of 833.3 μHz , which corresponds to a timescale of 20 min. variations.

From the PSD in Fig. 3, it can be seen that the magnitude of the fluctuations exhibited on all timescales tends to be reduced as the wind farm size is increased, the exception being the slightly lower reduction displayed by the “Large” wind farm size when compared to the “Medium” wind farm size on timescales between 1 week and 1 day. The different wind farm sizes exhibit similar levels of power fluctuation reductions on longer timescales, however at frequencies greater than approximately 23 μHz , the magnitude of power fluctuation reductions exhibited by the different profiles begins to differ noticeably. Since all of these wind farms are located within the same geographical area (Tehachapi Pass), it makes sense that the different size wind farms will experience similar magnitudes of power fluctuations at longer timescales (daily, weekly, seasonal).

The larger reduction of average power fluctuation magnitudes for larger wind farms at higher frequency is expected due to the filtering effect that provides buffering between changes in the wind speed and the farm power output, since for a sufficiently sized wind farm (land area basis), fluctuations in wind speed are not uniformly distributed amongst the turbines. For example, wind gusts may only affect certain sections of a farm or counterbalancing gusts may coincidentally increase and decrease output from various parts of a farm. It is important to note that these characteristics only provide buffering on timescales from 20 min to 12 h, depending upon farm size.

Therefore, the typical magnitude of the fluctuations experienced by a wind farm on fast to moderate timescales will decrease when the farm size is increased on a land area basis. These filtering effects are magnified at higher frequencies of variation, as displayed in

Fig. 3. PSD of different wind farm sizes. Reference signal: currently installed wind farm.

Fig. 3. At the fastest timescale (20 min), the degree of physical power fluctuations is decreased by 68.4% (–10 dB difference) by increasing the farm size from the currently installed size to that of the entire potential map. Note that the variability of the power profile for the “Large” wind farm exhibits slightly lower reductions in the magnitude of power fluctuations at frequencies greater than between 1 and 11 μHz compared to the “Medium” representation. This is due to the fact that the “Large” representation is comprised of a larger fraction of turbine sites that have a much higher yearly capacity factor than the “Medium.” These higher capacity sites tend to regularly vary over larger power ranges. For sites with higher capacity factors, the average power is increased, as well as the cumulative amount of time that the wind farm is producing maximum power, however regardless of capacity factor, there will regularly exist times when the wind farm is producing no power. Therefore, a similarly sized site with a higher capacity factor can be expected to exhibit slightly larger average fluctuations in power on the timescale that it varies between maximum and minimum power, which in this case is the multi-day timescale. In general, however, the magnitude of the power fluctuations from a wind farm decreases with increasing farm size due to both inertial and spatial distribution effects.

3.4. Effects of wind farm location-regional dispersion

From the results of the wind farm size study, it was postulated that the typical degree of power generation dynamics that a given wind farm exhibits is a function of its land area size. Larger wind farm sizes decreased the level of power generation dynamics by decoupling the effect of wind speed perturbations that occur in one area of the farm from affecting the power output of the rest of the farm. This concept also applies to the dispersion of wind resources over different geographical regions. The behavior of wind speeds in a given area is highly dependent on the geographic properties of that area and its surroundings, and therefore each wind resource area will tend to exhibit different characteristics in terms of daily profiles and generation dynamics, and therefore the different regions are decoupled from each other to a limited but noticeable extent. Because of this, it is possible that synergies may exist between the characteristics of different regions that may aid in mitigating the unfavorable intermittency characteristics of wind power generation. An investigation into these possible synergies for the Southern California region is presented here.

Fig. 4 displays a map of Southern California wind resources, including the location of four different sites that exhibit high wind potential: the Tehachapi Pass, the Beaumont region, the Palmdale/Lancaster area, the Granite Mountain site near Apple Valley, and the San Geronio Pass.

The power generation profiles for each of the wind farm sites were obtained by utilizing the same method that was applied to obtain the wind farm profiles previously. An analysis of the levels and timescales of each of the wind farm site profiles is determined by applying a PSD estimation for signals representing the successive aggregation of the different wind farm potential regions until the entire Southern California region is included, as shown in Fig. 5. The PSD estimation is carried out in reference to the power spectrum of the Tehachapi wind potential region.

In a similar fashion to increases in wind farm size within a particular potential region, the average magnitude of wind power fluctuations is reduced on all timescales as more wind potential regions are added to the aggregate profile, with that of the entire Southern California region exhibiting the largest reductions due to the increased degree of wind intermittency decoupling.

However, in contrast to the wind farm size study, the largest reductions in power fluctuations did not occur on the fastest

Fig. 4. Location of Southern California wind resources.

timescales. The degree of physical power fluctuations exhibited by a dispersed set of wind resources in the Southern California region is substantially lower than that of the Tehachapi wind potential region on timescales between one day and 1 h, with the largest difference of -4.3 dB (39% reduction) occurring at about $160 \mu\text{Hz}$, or 1.75 h timescale. This indicates that there exists notable, systematic counterbalancing between the different geographical regions in the Southern California region, that is, when one of the regions experiences a drop in wind power output on that timescale, another region experiences a corresponding increase. From examination of the regional geography, reductions on this timescale

make sense in terms of the time required for a fluctuation in the regional winds to propagate from one wind farm to the next. In the Southern California region, high winds are created by the pressure systems moving in from the Pacific Ocean and the jet stream and interacting with the mountainous geographical features that surround the California desert region, which create a “nozzle-like” region between Tehachapi and Palmdale for weather systems that approach from the coast. After the air masses move through the “nozzle” region, it expands into the desert region. Therefore, the westernmost wind potential regions are generally the first to experience changes in incident wind patterns, and that disturbance takes a certain time to propagate from the westernmost to easternmost wind farms, a time which is dependent on the wind speed. For example, at the average, rated wind speed of 15 m/s , it would take a disturbance in incident wind approximately 1.5 h to travel from Tehachapi to Beaumont. Therefore, it is not unreasonable for the largest reductions in wind power fluctuations to occur within that particular frequency range.

In addition, it is important to note that large reductions in physical power fluctuation magnitudes still occurred on the fastest timescales (-3.6 dB difference or 34% reduction), although this reduction is due to a statistical effect as opposed to a systematic one: a larger amount of non-deterministic component signals in the aggregate yields an increased probability of counterbalancing. It is also of interest to note that the shape of the reduction curves obtained from local aggregation of wind resources with respect to frequency does not change, also indicating that the frequency distribution of the power fluctuation reductions is a characteristic of this region.

While there clearly exists counterbalancing on the moderate (hourly, multi-hourly) to fast (sub-hourly) timescales, there does not appear to be much synergy amongst the farms considered here

Fig. 5. PSD of wind farm power profiles for regional aggregation. Reference signal: Tehachapi wind potential region.

at the longer timescales. To explicitly examine this further, the average seasonal profile and average daily capacity factor profile for the month of July for each of wind farm sites and for the entire Southern California region are presented in Fig. 6.

Note that both seasonal and typical daily profiles share very similar characteristics for all of the farms considered, which underscores the fact that inherent counterbalancing of wind power cannot be accomplished by wind farm dispersion alone in the Southern California region. While wind resource areas within the Southern California region are decoupled in one manner due to the differences in geographical features from site to site, coupling still exists in another manner due to the fact that regional weather events affect all of these areas simultaneously.

However, the dispersion of wind resources need not be limited to a particular geographical region. The dispersion of wind resources can be taken to a larger scale by interconnecting wind power from different parts of the country to potentially garner increased reductions in the magnitude of the aggregated wind power dynamics. In this section, wind farms governed by completely different weather patterns, as opposed to different geographical features, are examined. In order to carry out this analysis, aggregated power profiles were created by combining the entire Tehachapi wind potential region with other similarly sized wind farm potential regions in Southern Wyoming and New Mexico. In addition, the Southern California Region is included for comparison, as well as a total aggregated wind profile consisting of the combination of the Southern California Region profile and similar sized wind farm regions in Southern Wyoming and New Mexico was created, designated as “Western U.S.”. The PSD estimation for the wind power output of each of these aggregated wind farms is presented in Fig. 7. The power spectrum of the Tehachapi wind potential region is once again used as the reference signal.

An examination of Fig. 7 reveals that when compared to the reference signal, the reduction in the magnitude of power fluctuations garnered by interconnecting wind farms that are governed by different weather patterns is dependent on timescale. In contrast to the previous results, the profile of the reduction curve changes depending on the particular wind farm used in the aggregation. On the daily timescales, aggregation with Southern Wyoming yields significant power fluctuation reductions, to a larger extent than even the entire Southern California Region, while aggregation with New Mexico yields power fluctuation reductions on par with that of the entire Southern California region. However, on hourly timescales, the same aggregations yield almost no reductions in power fluctuations, especially when compared to those garnered by the Southern California region and aggregation with Beaumont. On the fastest timescales, aggregation with New

Fig. 7. PSD of aggregated wind power output, large dispersion. Reference signal: Tehachapi wind potential region.

Mexico only yields a small reduction in the magnitudes of power fluctuations. This occurs even though the size of the aggregations (Tehachapi + Beaumont, Wyoming, or New Mexico) is the same.

This behavior can be explained by examining the properties of the power signal from each individual wind potential region used in the aggregation. A representative two week time series plot of each component wind potential region as well as the aggregated Western U.S. representation is displayed in Fig. 8.

This period was found to be representative of the properties of each individual power signal for the entire year. The Tehachapi and Beaumont wind potential regions, which are adjacent to each other and governed by the same weather phenomena, exhibit the similar properties such as strong, regular daily variations with infrequent fluctuations on faster timescales. Southern Wyoming tends to exhibit frequent but small variations on the hourly and sub-hourly timescales, with a daily profile that exhibits a lower power range, degree of consistency, and some counterbalancing characteristics when compared to Tehachapi and Beaumont. New Mexico tends to exhibit an inconsistent daily profile, with large power fluctuations occurring at high frequencies.

When two wind farms are interconnected, the properties of one power signal is imposed onto that of the other, and their significance in the normalized profile is reduced to an extent determined by the relative contributions of the two signals. Since Tehachapi and Beaumont share essentially the same properties in terms of power fluctuations, combining the two simply reduces the

Fig. 6. Regional average a) seasonal and b) daily profile comparison for July.

Fig. 8. 2 week power profile of different wind potential regions – July 2005.

magnitude of the power fluctuations in a manner similar to the previous result. Southern Wyoming exhibits relatively weak daily variations when compared to Tehachapi. However, those variations frequently occur out of phase and act to counterbalance the profile of Tehachapi, therefore combining the two will result in a large decrease in the magnitude of the power fluctuations experienced on the daily timescale. In this right, it makes sense that the reduction is larger when compared to the aggregation of the entire Southern California region, since the Southern California region is governed by the same weather phenomena and therefore experience the same trends of daily power fluctuations. In addition, the Southern Wyoming wind potential region exhibits much stronger variations on the hourly timescales when compared to Tehachapi, therefore the aggregation will result in only a slight decrease in the magnitude of the power fluctuations experienced on those timescales. New Mexico exhibits no consistent daily profile but strong power fluctuations on fast timescales, therefore aggregation with Tehachapi will only garner very small reductions in the magnitude of power fluctuations on those timescales. However, the aggregation of all component wind farms allows the composition of a wind power profile that is smoother overall when compared to any of the individual component wind farms. During events of large power fluctuations in the individual wind farms such as those exhibited by New Mexico between the 40th and 60th hours, or between the 90th and 110th hours in Fig. 8, the aggregated power profile was only slightly affected.

From this data, it is clear that the effect of increasing the dispersion of wind resources is only predictable if it occurs across a region that is governed by the coupled weather phenomena. In that case, the effect of increasing dispersion is straightforward: higher dispersion reduces the magnitude of the power fluctuations noticeably on all timescales, with the most significant reductions occurring at a particular timescale range which is a characteristic of the regional geography. This occurs because moderate and fast timescale intermittencies such as gusts and weather disturbance propagation are governed by features such as the local geography, and dispersion allows different parts of the wind resource to be decoupled in terms of those features. However, if dispersion occurs across a region which includes wind resources that are governed by completely different weather phenomena, the effect is not immediately clear. The properties of each wind potential region must be examined individually to obtain a sense of how the use of dispersing wind resources across that region will affect the aggregated dynamics.

Overall, utilizing multiple wind resource locations to increase dispersion can produce a noticeable reduction in the magnitude of the typical or average power fluctuations experienced by the electrical grid at shorter timescales (6 h or less) of wind resources that are geographically adjacent to one another and governed by the same weather phenomena. This is very beneficial for reducing the day by day requirements on the operation of the supplementary generators or other technologies on the same electrical grid. However, at longer timescales, increasing dispersion does not provide benefits in terms of reducing the dynamic requirements of balance generation.

4. Conclusions

A characterization of the behavior of wind power generation in the Southern California region has been carried out to determine the implications for balance generation. The sensitivity of a wind resource's dynamic characteristics and power range to farm size and regional dispersion were investigated. The key conclusions of this study are as follows:

1. Increasing the size of a wind farm brings about significant decreases in the magnitude of the power fluctuations exhibited by that resource on timescales shorter than 12 h, and provides a filtering effect that buffers the quick changes in wind speed from affecting total farm power output.
2. Increasing the wind farm dispersion throughout a geographic region that is governed by coupled weather phenomena reduces the relative magnitude of wind power fluctuations, with the largest reductions taking place in a timescale range which is a governed by regional geography. However, the effect of increasing the wind farm dispersion throughout regions governed by decoupled weather phenomena is not straightforward and the dynamic properties of the different regions must be examined in detail to determine their effect on the magnitude of the aggregated power fluctuations.

Novel energy management strategies will have to be developed to manage wind power's intermittencies and increased levels of dynamics. Wind power can make relatively economical contributions to an overall renewable energy portfolio. However, moderate to high use of wind power in an electrical grid of any size must be managed and supplemented by balance power, the simultaneous implementation of complementary renewable sources, energy storage and/or management to counter wind power intermittency and dynamics. This study motivates the need for a holistic approach to attaining the goal of high levels of renewable energy penetration. The benefits and deficiencies of other renewable resources, and the analysis of holistic approaches to attaining high levels of overall renewable penetration into the electrical grid and identifying the types of complexities required to manage renewable power resources on the grid are the focuses for future work.

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