Building a Smarter Smart Grid Through Better Renewable Energy Information

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***Abstract*—Smart grids are a relatively new development in power systems and due to the possible complexity of such systems; the possibilities have yet to be clearly defined. Drawing a clear distinction between one grid configuration being “smart” and another failing the criterion is not realistic. Instead, it is much more practical to consider smart grids in terms of opportunities to improve the operation of the power system that are exploited or can be exploited. One of the keys features of a smart grid is the ability to utilize information to make better operational decisions. This paper proposes that significant improvements can be made to the operations of a smart grid by providing information about the likely behavior of renewable energy – either through online short-term forecasting or longer-term assessments.**

***Index Terms*—Smart grid, renewable energy, forecasting, assessment.**

I. Introduction

ONE of the fundamental challenges of power system operation is running a *true* supply-on-demand system that is expected to be absolutely reliable. Historically this challenge led to a power system based on highly controllable supply to match a largely uncontrolled demand. However, with the dual concerns of climate change and energy security alternative sources of energy have become an increasingly attractive proposition and are now beginning to achieve significant levels of penetration in certain areas. This can cause problems with the conventional system balancing methodologies. Since penetration levels of renewable energy are likely to continue increasing a rethink of the existing energy balancing paradigm may be required. Fortunately, an operational smart grid has the potential to mitigate some of the difficulties that are posed by high levels of renewable energy generation.

The use of smarter grid operations allows for greater penetration of variable energy sources through the more flexible management of the system. This can be achieved in many ways from active demand-side management (DSM) to temporary storage technologies, whether dedicated to electricity or sourced through a symbiotic supply (such as electric vehicles).

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One of the key aspects to a smarter grid is the ability to make decisions on how to operate the power system on *both* the supply-side and the demand-side. The right information is essential in order to make the right decisions and this is ubiquitous throughout the entire smart grid system.

II. Smart Grids

The term “smart grid” is somewhat qualitative since there are various proposed implementations that have varying levels of sophistication [1..5]. However, standard among all implementations is the use of advanced sensor and communications technologies to enable better use of assets, provide improved reliability and enable consumer access to a wider range of services. There are some defining features that exist in most smart grids.

A. A smart grid will provide an interface between consumer appliances and the traditional assets in a power system (generation, transmission and distribution)

This two-way communication will allow the consumer to better control their energy usage and provides more choices to the customer. Furthermore, the two-way communication will also allow better DSM such that in certain situations the system operator can be given control of the loads in the system enabling more agile responses to system behavior.

B. A smart grid will be at least semi-autonomous

The use of intelligent systems will enable the power system to respond to stimulus, observed through sensor networks, with limited input from a human. This will enable much faster operations when handling interruptions in the power system and may even be able to identify areas of concern and reconfigure the power system to mitigate potential contingencies.

C. A smart grid will optimize the assets of the power system

The use of responsive operating protocols will optimize power flows along existing transmission thereby improving the reliability of the system and deferring capital expenditure on transmission upgrades. Due to the communication of peak load periods and the likely subsequent consumer response to increased price signals the peak loads will be reduced and the need for expensive flexible generation technologies will be reduced.

D. A smart grid will support better integration of distributed generation into the conventional centralized power system

Improved communications and more advanced metering technologies will enable more intelligent incorporation of decentralized power production through the use of better sensors and two-way metering. This will allow customers (whether residential, commercial or industrial) to re-evaluate the proposition of connecting local generation equipment. The customer could in fact be an energy supplier instead of consumer.

III. Renewable Energy Integration Using a Smart Grid

Weather-driven, non-scheduled, renewable energy sources require new operational procedures. Conventional fossil fuel power plants can be operated in accordance with the needs of the power system; the present power system operating procedures were designed with this in mind. Renewable energy sources such as wind or solar are variable and thus the operating schedules of such plants are largely dictated by the changing "fuel" supply. This is especially pertinent in the case of wind, photovoltaic solar and run-of-the-river hydro, none of which have inherent storage in their power plant design. These systems cannot be controlled in the same manner as a conventional generation facility.

With low levels of wind or solar energy penetration the overall effect on grid operations is limited, yet as the penetration levels increase so too do the effects. It has been recognized that as the penetration levels increase, more advanced control of the power system will be required to maintain system reliability [6]. These controls include more efficient use of transmission, use of demand response and intelligent energy storage, all of which can be enabled through the application of a smart grid. In fact, the ability to better integrate renewable energy is one of the driving factors in some smart grid installations. Xcel Energy's SmartGridCity white paper specifically communicates that a key aspect to its renewable energy integration plan involves a smart grid:

> *"The ability to communicate (via a smart grid) and new improvements in storage (cheaper, longer lasting, higher capacity batteries) allows for a creation of a new market instrument. A smart grid with advanced energy storage reduces the variability associated with renewable energy, enabling more renewable energy on the grid, thus reducing emissions."*

IV. Assessing Renewable Energy in a Smart Grid

A smart grid must be able to make decisions and those decisions must be based upon information. However, not all of that information is necessarily "live" data. In fact, when designing a smart grid the likely limitations on the system must be understood – some of these limitations will be physical, some will be contractual and some may even be political. Without enabling the smart grid to properly handle these limitations, the smart grid would not perform correctly. For example, a smart grid may allow for load curtailment, but no consumer is going to be happy to accept such an agreement without some guarantee of a maximum number of interruptions. Similarly, storage may be purchased to allow for better operation of localized portions of the power system (taking strain off transmission during constrained periods) or even utilizing storage that is designed to support the power system as a whole. Alternatively, the storage may be sourced from an electric-vehicle-to-grid arrangement, but again an agreement must be made on how often the system can cycle the batteries and how much it is allowed to draw them down. Such system design decisions, whether in terms of contractual agreements or the installment of physical equipment, must be based on accurate information about the degree of flexibility that is required. If high levels of non-scheduled renewable energy are employed in the system, these will tend to dominate the flexibility requirements and so careful assessment of the renewable energy resources is vital when setting-up a smart grid, re-negotiating contracts or considering installation of physical equipment. In essence, an assessment of the variability of renewable energy and the effects on the power system must be performed.

Integration studies are continuing to improve and as the level of sophistication increases, so too does importance of accurately modeling the "fuel" that drives the renewable energy [8]. In order to assess the likely behaviour of long-term patterns the best information we have about the future is what has happened in the past. Unfortunately, long-term records of renewable energy production are not available for a vast majority of the generation plants. Most plants have only been operational for a few years at most and the growth rate of new renewable energy is still a significant portion of total installation. In fact, it is usually not even possible to obtain long-term, on-site meteorological data [9]. Thus, an alternative must be used to be able to obtain the historical information used to determine the requirements for the smart grid. IEEE Transactions on Power Systems had a Special Section on Wind Energy in 2007 including the paper "Utility Wind Integration and Operating Impact State of the Art" [10] which stated:

> *"A state-of-the-art wind-integration study typically devotes a significant effort to obtaining wind data that are derived from large-scale meteorological modeling..."*

In fact, one of the strongest advantages of using numerical weather prediction modeling to downscale reanalysis datasets is that long-term records can be obtained. It is possible to perform a 40-year climate variability analysis, detailing the hour-by hour wind and power capacity at a site. This level of detail may not be warranted for small energy installations , but for large installations (or even high concentrations of small installations) this information can be used to develop some key decision making tools that allow the optimization of the system design for the smart grid.

A. Daily Variability

Each renewable energy project (or region) has specific variability patterns that are typical depending the time of day and time of year. The energy output is based on the local weather patterns, which change depending on the seasonal and daily influences. After performing a record extension over a period of 40 years the average behavior in terms of monthly diurnal cycle can be established. Fig. 1. shows an example of a site with diurnal cycles defined for each month. The figure shows that highest generation occurs between 0400 and 1200 UTC in spring and summer (it is a site from the northern hemisphere). However, the lowest generation typically occurs in summer from 1500 to 0100 UTC. This clearly demonstrates that the winter production tends to have a fairly low difference in its diurnal behavior while in summer the diurnal behavior is marked. The variation in the diurnal cycle during summer would be something that should be addressed in a smart grid.

Hour of Day (UTC)	Jan	Feb	Mar	Apr	May	Jun	Jly	Aug	Sep	Oct	Nov	Dec	Avg
0	45.8	41.3	44.5	45.7	38.8	29.4	19.3	15.5	21.2	32.1	42.8	47.4	35.3
1	50.1	45.6	47.6	45.4	39.6	35.0	25.1	23.4	29.3	40.0	47.6	51.3	40.0
2	52.8	49.5	52.5	51.5	48.7	48.0	38.9	35.2	39.4	47.0	51.1	54.0	47.4
3	54.5	51.9	56.4	56.6	57.1	59.3	51.9	46.8	47.7	52.1	53.3	55.6	53.6
4	55.5	53.7	58.5	59.8	61.7	65.0	61.4	55.2	53.2	55.3	54.5	56.5	57.5
5	56.4	55.2	60.2	62.4	64.1	69.2	66.7	59.5	55.5	57.2	55.4	57.2	60.0
6	56.7	56.4	61.1	64.2	66.0	71.7	68.9	61.2	56.6	58.5	55.8	57.6	61.3
7	56.9	57.4	61.9	65.7	67.7	73.4	69.9	62.6	57.3	59.5	56.5	57.9	62.2
8	57.0	57.9	62.0	65.9	68.0	73.4	68.9	62.1	56.9	59.2	56.2	57.7	62.1
9	57.4	57.9	62.1	65.7	67.4	71.8	66.6	59.8	55.2	58.6	55.4	57.5	61.3
10	57.6	57.8	61.6	65.2	67.3	70.0	63.8	56.8	53.5	57.4	55.3	57.2	60.3
11	57.4	57.3	61.2	64.2	66.1	67.7	60.3	53.0	50.9	55.9	55.2	57.0	58.9
12	57.5	56.9	60.4	62.6	64.2	65.2	56.5	49.0	48.2	54.8	55.2	56.8	57.3
13	58.2	57.2	59.5	61.0	57.5	54.8	47.5	44.3	46.1	55.2	56.1	57.0	54.5
14	58.0	55.8	56.2	53.3	47.6	45.9	36.8	29.8	37.0	52.5	55.3	56.7	48.7
15	55.1	50.6	50.3	50.4	45.2	41.1	31.3	25.9	30.4	43.8	51.9	54.6	44.2
16	47.5	44.7	49.4	50.1	42.5	34.5	23.5	19.5	27.3	39.2	45.2	47.6	39.2
17	45.7	45.3	50.1	49.0	38.7	29.1	17.3	14.0	23.7	37.9	44.4	43.8	36.5
18	46.5	45.6	49.5	47.3	35.2	25.2	14.0	10.9	19.9	35.7	45.0	45.1	34.9
19	46.6	45.3	48.8	46.3	33.8	22.9	12.4	9.7	17.6	33.5	45.1	45.7	33.9
20	46.2	44.9	48.2	46.4	33.7	21.7	11.8	9.0	16.5	31.9	44.6	45.3	33.3
21	45.3	44.5	48.1	47.2	34.7	22.0	11.7	9.5	16.5	31.2	43.8	44.8	33.2
22	43.9	43.9	48.6	47.8	36.4	23.5	13.1	10.8	16.7	31.4	42.5	43.5	33.4
23	42.5	41.7	47.6	48.5	38.4	25.8	15.3	12.2	18.1	30.9	40.0	42.8	33.6
Avg	52.1	50.8	54.4	55.1	50.8	47.7	39.7	34.8	37.3	46.3	50.3	52.1	47.6

Capacity Factor: < 20, 40, 60, 80 %

Fig. 1. Daily variability graphic showing the long-term averaged diurnal cycles, defined separately for each month. It also provides a yearly average indicating the overall diurnal cycle and monthly cycle of the site.

B. Monthly Variability

Even though the monthly variability may be understood in a general sense from Fig. 1. the difference in behavior in the same months in different years is also important to understand. The variability assessment over a period of 40 years generally defines the average behavior reasonably well, yet this does not mean that every month will behave exactly as its long-term mean would indicate. Fig. 2. shows an example of a month-to-month climate variability analysis. The figure shows that during August the lowest output is expected and there have been months where the energy production was nearly as low as 15% of the capacity factor. However, the median energy production in July is also comparably low, but there was at least one instance where the capacity factor was almost 70%. This variation is important to understand when designing a smart grid system.

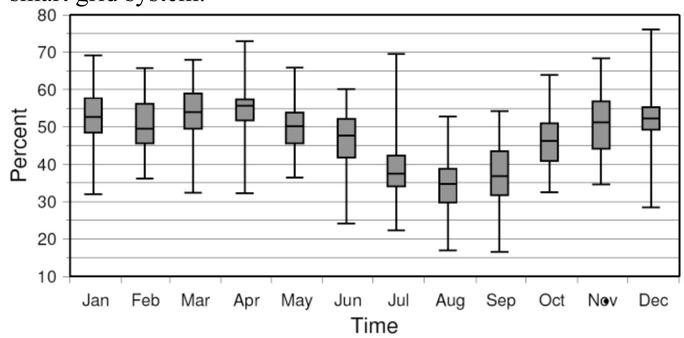

Fig. 2. Month-to-month climate variability analysis showing variable power capacity derived from a 40-year dataset. The solid line within the shaded box denotes the median power capacity. Upper and lower boundaries of the shaded box correspond to the 75% and 25% quartiles, while the extremities denote the maximum and minimum power capacity.

C. Yearly Variability

Similarly to the monthly variability, each site also has variable output from year-to-year. If a renewable energy plant is being relied upon to produce energy for the system, it is useful to know the level of variability that might be faced from year-to-year. Fig. 3. shows an example of a year-to-year climate variability analysis – this example has a comparably consistent energy production from year-to-year.

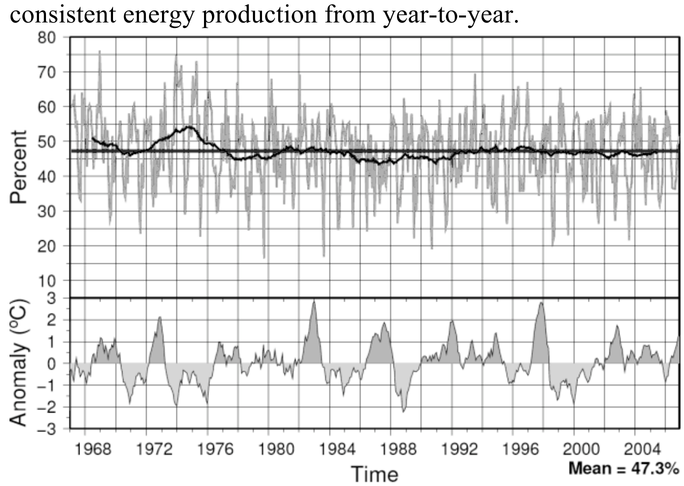

Fig. 3. Month-to-month climate variability analysis showing variable power capacity derived from a 40-year dataset. The top panel shows a time series of monthly-mean power capacity in gray and a running 36-month mean in black. The straight black line is the long-term average. The bottom panel shows the time series of monthly-mean El Niño 3.4 anomalies.

V. Forecasting Renewable Energy in a Smart Grid

When actually operating smart grids forecasts of future requirements are essential to be able to prepare the flexible systems to behave in the appropriate manner. Non-scheduled renewable energy resources add another variable to an already complicated balancing act. The fact that these sources of generation cannot be dispatched in the traditional sense can cause problems for conventional system operation. A smart grid takes advantage of potential improvements that can be made to conventional operation through the use of communications and information. While renewable energy cannot necessarily be operated in a conventional manner, its behavior can be predicted and the forecast information is exactly the kind of information that a smart grid must use to improve system efficiency. In fact, as renewable energy penetration levels continue to increase, non-scheduled renewable energy may become the single largest source of variability on the power system. This makes the employment of accurate renewable energy forecasting a key component of a smart grid. In a smart grid, decisions are dynamically made based on information about electricity supply and demand. In the world of renewable energy integration, forecasting feeds the smart grid.

Meteorological processes drive renewable energy generation and thus it is inherently variable. This variability occurs across all of the time frames of utility operation from real-time minute-to-minute fluctuations through to yearly variation affecting long-term planning (as demonstrated above). However, recent wind integration studies have shown that the variations that have the largest effects on the system reliability operations and costs of operation are those in the hourly and daily timeframe [10]. These two times frames are directly related to the ancillary services of load following and unit commitment; consequently, the state-of-the-art wind energy prediction systems focus on these timescales in order to meet the needs of the systems operators and market traders. In a smart grid a lot of the human interactions that presently try to manage system operation will be able to be replaced by machines that have a faster response time and can process larger quantities of data.

In fact, even in a conventional power system forecasts of renewable energy are considered crucial once even moderate levels of penetration are achieved. During real-time operations, the generation and the load must be matched. The conventional generation can be controlled to a large extent, but the load and the renewable energy generation must be forecast; there is no other efficient way that the conventional plants can be operated to provide the balancing. Furthermore, the uncertainty of the forecast is also vital to understand in order to be able to estimate the necessary reserve capacity for the system, following reliability and frequency control requirements. The ability of a smart grid to process this kind of information could result in significant improvements in the operation of renewable energy resources. Fig. 4., Fig. 5. and Fig. 6. show a range of forecasts with different horizons. Fig. 4. shows a plot of an hours-ahead forecast primarily based on observations information. This plot includes a portion of the plot showing the recent performance of the system. The rapid change in wind energy output was well-forecast and a smart grid could have used this information to accurately account for the changing output from the renewable energy plant. Fig 5. and Fig. 6. show plots of longer forecasts that are predicting the day-to-day behavior of a wind energy plant (including prediction intervals). As can be seen from these plots even when the winds are rapidly changing there is still significant information that can be obtained about the future output from a renewable energy plant. Then, as the forecast goes further out into the future (for the week-ahead plot) the prediction intervals widen indicating a corresponding reduction in the level of confidence in a forecast so far into the future.

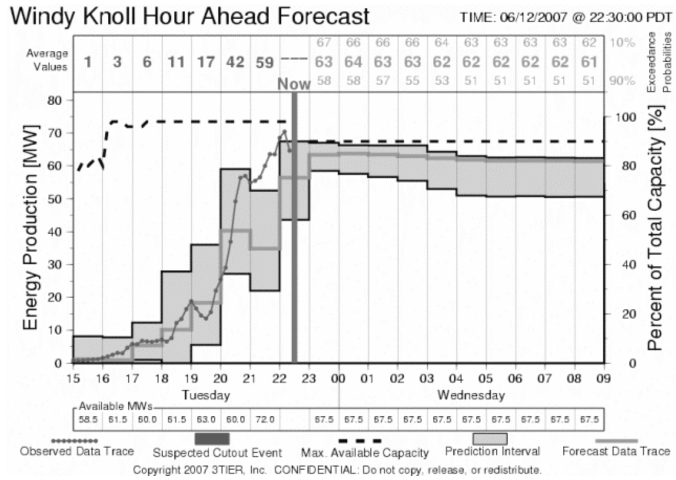

Fig. 4. Plot of hour-ahead forecast information. The line in the middle of the shaded area is the forecast, the line with circular markings to the left of "Now" shows the observations.

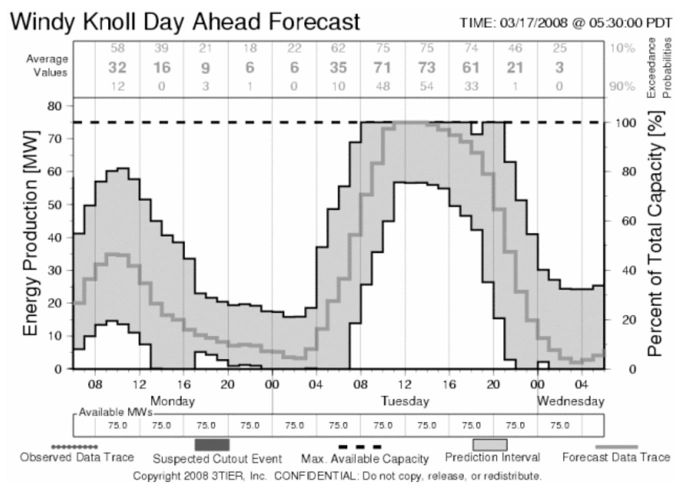

Fig. 5. Plot of the day-ahead forecast information.

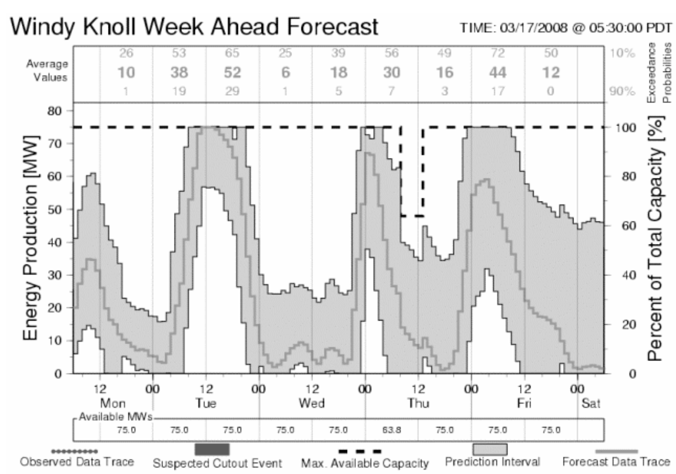

Fig. 6. Plot of the week-ahead forecast information.

In fact, the use of a smart grid will also improve the forecasting of renewable energy. The state-of-the-art forecasts process large amounts of data and the more reliable and timely the data transfer, the greater the accuracy of the forecasts – especially for the hour-ahead forecast range. The day-ahead forecasts are typically created in a similar way to the assessment work mentioned previously using numerical weather prediction models to downscale information from coarse resolution global weather models. These models are tuned using data if that data is available. In a smart grid, the data would certainly be available. However, it is the hour-ahead forecasts that help with the load following of the power system that gain the most in a smart grid. Typically the hour-ahead forecasts employ statistical methods primarily based on the most recent observations. The first phase in developing this type of forecast consists of identifying, compiling and integrating data from a wide variety of sources: location of turbines and anemometers, available observation records, etc. The second phase consists of developing and training various self-learning forecasting methods using all the available data. The final product provides a timely, relevant and accurate forecast. Taking advantage of a vast communication network the forecast of renewable energy will be able to utilize this information from an even wider set of sources. Furthermore, it also opens other opportunities such as using weather forecasting information to forecast transmission line ratings to allow for the dynamic rating (and planning) of transmission will allow a much more efficient use of the existing infrastructure.

VI. Conclusions

A smart grid has the potential to revolutionize the power systems operations, a revolution that will need to occur if very large penetrations of renewable energy are to be incorporated onto the grid. However, in order to efficiently operate and make the best decisions, a smart grid must have information. As the penetration of renewable energy continues to increase, the variation of such energy sources may become the single largest source of variability on the power system. Understanding this variability is vital. The variability must be understood in terms of long-term behavior through assessments of the long-term weather patterns that would affect the locations of renewable energy generation. This information can be used to develop better procedures and capabilities for the smart grid. The variability must also be understood in terms of short-term behavior affecting the unit commitment and load following reserves. This short-term generation variation can be forecast using state-of-the-art techniques on both these key timescales.

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VIII. Biographies

Cameron W. Potter (S'03, M'06) graduated from the University of Tasmania, Hobart, Tasmania, Australia with a Ph.D. in Power Systems Engineering and Artificial Intelligence. Cameron also attained his BE with First Class Honours from the University of Tasmania, Hobart, Tasmania, Australia.

Cameron presently works as the Managing Director of 3TIER Pacific Rim Pty Ltd. His employment experience also includes working for 3TIER Inc. in Seattle, U.S.A. as a Power Prediction Engineer, for the University of Tasmania as a Laboratory Supervisor and Tutor at and as a Technical Assistant at Hydro Tasmania. His special fields of interest include the application of artificial intelligence, data mining and non-deterministic methods to practical renewable energy engineering problems.

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Ken Westrick is the founder and CEO of 3TIER. Prior to founding 3TIER in 1999, Westrick earned both bachelor and masters degrees in atmospheric sciences from the University of Washington and was an integral member of the University's PRISM Project, where he specialized in weather and environmental forecasting techniques and computer modeling strategies. Westrick also served nearly 14 years in the US Army, including tours with the US Army Ranger Regiment and Special Operations Command.