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GRID OPERATIONS WITH HIGH PENETRATION OF PHOTOVOLTAIC SYSTEMS

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ABSTRACT

Integrating variable generation sources such as utility-scale photovoltaic (PV) plants into the electric grid is desirable with the increasing quest for cleaner sources of electric power generation and reducing cost of utility-scale PV. As a result, solar market in the United States has more than doubled over the past two to three years, but looking ahead, systemic challenges to growth loom both in the near term. Real-time grid operators are especially concerned about large-scale PV systems operating under cloudy conditions and large disturbances. This paper provides an overview of the computational and optimization research carried out at the Real-Time Power and Intelligent Systems Laboratory to address some of the grid operational concerns with high levels of PV penetrations.

INTRODUCTION

The solar energy market has been growing rapidly during the last decade, especially in the grid-tied photovoltaic (PV) market sector. Over the past few years, solar PV has moved light years ahead of where it stood in the first half of 2012. Between 2012 and 2014 in the United States (U.S.), cumulative residential and non-residential installations have both doubled while cumulative utility PV installations have more than quadrupled. With renewable energy regulation passed in many countries including Australia, Canada, China, Germany and U.S., utility-scale PV plants ranging from 5 MW to more than 250 MW are in either operation or planned to be in the near-term [1,2].

The most straightforward way to reduce carbon footprints is to simply use less power. By its distributed nature and presence, solar allows utilities to employ 'smart grid' technologies more efficiently including distributed energy storage.

Although the U.S. solar market has more than doubled over the past two years, looking ahead, systemic challenges to growth loom both in the near term. If PV penetration become significant fractions of the connected generation, it is no longer appropriate for the PV generators to be considered as a "negative load". They must take part in the operation of the power system. A major challenge in integrating high penetrations (>20%) of solar-energy rests in a grid's ability to handle the intrinsic variability of solar power.

The reliable and secure operation of power systems with a high penetration of renewable energy resources raises concerns. High photovoltaic (PV) penetration levels can significantly affect both the stability of the systems since the sun does not shine on demand [3]. In order to maximize the penetration of renewable energy, alternative power or demand side management technologies are needed. These sources could include energy storage, a tie to a neighbouring power system with excess generation, preferably from clean sources, etc. PV power is difficult to predict and depends primarily on weather conditions and cloud movements. A cloud cover passing over a PV plant is like a loss of a generator of the size of the PV plant. Furthermore, PV plants usually are connected to the grid through power electronic converters, which reduces the system inertia unlike conventional generators [4]. The power and frequency fluctuations in systems with large MW PV plants raise dynamic and transient stability concerns [5, 6]. The rate of change of frequency (ROCOF) is increased as a result. When a frequency event occurs, the conventional synchronous machines will inject or absorb kinetic energy into or from the grid to counteract the frequency deviation. It is therefore critical to have dependence on power and energy sources that have fast charge and discharge characteristics. Ideally, battery energy storage and super capacitors will be perfect but this is only feasible for smaller power systems.

The development of revolutionary technologies such as distributed high-energy and high-power storage devices to handle the intrinsic variability of photovoltaic plant generation and enable high penetration levels while maintaining secure real-time grid operations are needed. Distributed energy generation/harnessing and distributed energy storage will revolutionize the way the electricity infrastructure is currently operated.

Real-time grid operators are therefore especially concerned about large-scale PV systems operating under cloudy conditions and large disturbances. Many of the concerns/issues with real-time grid operations will disappear as the bulk power generation supplies a constant load.

A recent advanced research projects agency – energy (ARPA-E) funding opportunity announcement was on network optimized distributed energy systems (NODES) [7]. The NODES program aspiration is to enable renewables penetration at the 50% or greater, by developing transformational grid control algorithms and architectures that optimize the usage of flexible load and DERs (distributed energy resources). The challenge is to reliably manage, locally or globally, while having minimal impact on customer quality of service (QoS).

Optimal power flow (OPF), or its security-constrained version, is based on steady-state optimization without considering local controller and load dynamics, and its optimal solutions are obtained based on inaccurate forecasts. Although the OPF provides optimal dispatches for the next forecasted period, any unforeseen real-time load/generation variation or post-contingency operation between two dispatch instants (typically 5 minutes apart) are handled by simple linear controllers or some predefined reactions with little, if any, system-wide optimization. For real-time active power balancing, the proportional-integral-controller-based AGC is typically used [8]. For reactive power support, locally-controlled reactive resources are typically used for voltage regulation, such as large generators equipped with automatic voltage regulators (AVRs), switched capacitor banks, on-load tap changing (OLTC) transformers, and flexible AC transmission system (FACTS) devices [8].

The present day separate secondary control loops for frequency and voltage are developed based on the assumption that only small variations and uncertainty exist in power systems during a short period of time, and long-term large variations are handled by sequential steady-state optimizations (e.g., OPF). This assumption is true when the only uncertain factor in a power system is the load, which varies relatively slow at the transmission level and is well predictable because of its cycling characteristics. However, in an environment with high variability and uncertainty, significant power flow redistribution may occur in a short period. With the present frequency and voltage control schemes, power line overloading and bus over/under-voltage may occur due to the limited control capability of AGC and limited local reactive power resources. A system-wide active and reactive power coordinated control algorithm is thus necessary in a high-variability environment. With the global dynamic information available through synchronized phasor measurement units (PMUs), advanced wide-area control schemes become possible to improve grid dynamics. The design of a system-wide automatic power flow controller to dynamically control a power system to its optimal operating point has received little attention to-date.

This paper presents a summary of the on-going research at the Real-Time Power and Intelligent Systems (RTPIS) Laboratory at Clemson University [9] on how to reliably and efficiently operate an electric grid in an environment with a high level of PV penetrations without impacting the customer's quality of service. The emphasis of the research at RTPIS lab in this area is in applying computational methods to power systems with PV plants in order to enhance grid operation. The rest of the paper presents studies on modelling and characterization of PV systems, prediction of PV power, tie-line bias control with large PV plants and optimal control of grid-independent PV systems.

CHARACTERIZATION AND MODELLING OF A GRID-CONNECTED PV SYSTEM

It is possible to estimate the power output of a PV system with use of predictive models when a set of meteorological inputs are available. In the United States, the most prominent set of weather data is the Typical Meteorological Year data (TMY2 or TMY3), and these data sets are parsed for data relevant to the particular model being used (e.g., irradiance, temperature, snow cover). The data are used in a predictive model to estimate system output parameters such as DC power, AC power, and module temperature. The predictive models may also be used to determine if a PV system is operating as expected, allowing system operators to determine maintenance schedules. In addition, they could be used to predict the performance of an existing system for calculation of expected-performance incentive rebates.

Existing modelling techniques require the characterization of a number of system components in order to produce model parameters. Characterization may be a lengthy process, depending on the model used. The characterization assumes that all components in the system are similar to the components which were tested to generate model parameters. Thus, current techniques have difficulty in quantifying unit-to-unit variation of each component, degradation of components, and other small factors such as resistive wire losses and shading.

A dynamic neural network such as a recurrent neural network (RNN) may be used as an alternative method of characterizing and modelling performance from a specific PV system. The RNN is able to use simultaneously sampled weather data and performance data over a period of time to learn the input/output relationships between weather and system performance. The RNN requires no information about the specific components of the modeled PV system. Instead, the RNN learns the relationship between input (weather) data and system performance by training itself on a data set with concurrent weather and performance data. The RNN may then make predictions about system performance when given weather data, even if the weather data was not in the training data set. Thus, the RNN method models the PV system in a holistic manner, rather than modeling individual components, and includes system loss factors such as those described earlier. However, since a set of concurrent weather and performance data is required, the RNN technique may only be used to model systems which are already in operation.

Detail modeling and characterization studies using RNNs is described in [10, 11]. Figure 1 and 2 shows the PV system studied and estimated versus measured AC power for one day with high variability, respectively.

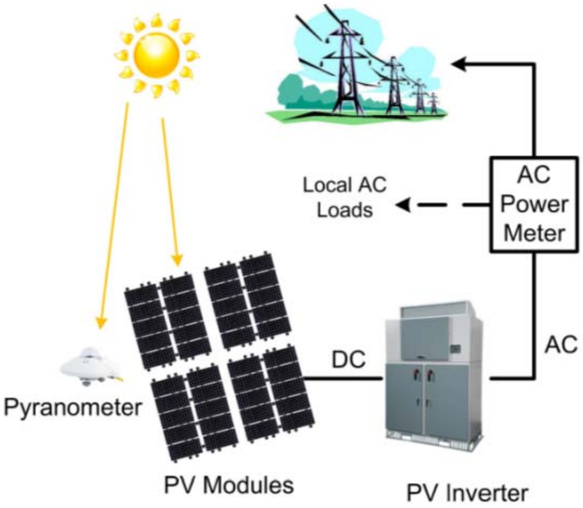

Figure 1 A typical grid-connected PV system [9]

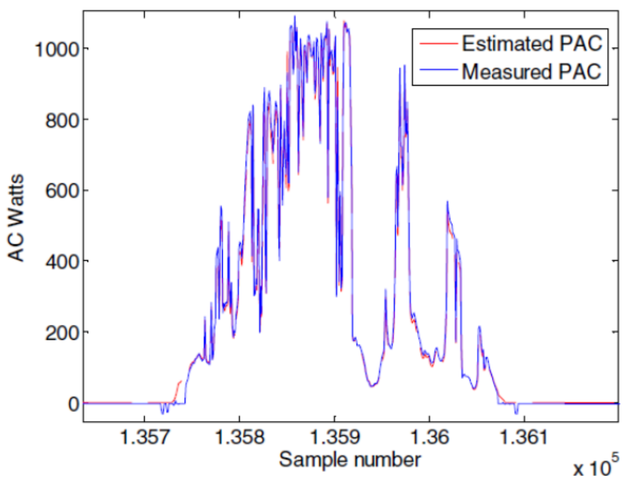

Figure 2 Estimated and measured AC PV power for day with high irradiance variability [9]

It is possible that the RNN characterization method may be altered to predict other output parameters (e.g. DC power, DC voltage, DC to AC efficiency) by simply adding additional output neurons. Additional data may be given to the RNN to increase the predictive power; useful data parameters may include solar time, airmass (or spectrum), or sun position.

PREDICTION OF PV POWER

Unexpected large variations of PV plant output can cause dynamic and transient stability concerns which may lead to the collapse of a power system. This increases operating costs for the electricity system and potential risks to the reliability of electricity supply. Predicting variations of the PV power generation is a potential solution to overcome these challenges. Very short term PV power forecasts for prediction intervals ranging from few seconds to a minute plus are very important in making decisions and improving performance of grid operations in electric utility control centers.

There are several methodologies proposed for long term and short term prediction of PV power. These methods include using mathematical equations, regression analysis and linear time series models [12-14]. These approaches are not accurate for PV power prediction, as independent variables changes in a non-linear stochastic manner. Most recent studies from the RTPIS Lab has shown that echo state networks (ESNs), a class of RNNs, developed by Jaeger [15] perform better and overcome neural network training difficulties. ESN has been used in predicting short to medium range prediction of solar irradiance [16] and PV power [17].

The study used in this study at the RTPIS Lab. is shown in Figure 3. A 200 MW PV plant made up of four 50 MW PV plants is connected to a two-area, four-machine system [8]. The 50 MW PV plants are connected to a 230 kV utility transmission grid through a double converter and transformer stage. The entire system, which consists of the power system, the PV plants (integrated in Area 2), frequency monitoring using phasor measurement units (PMUs), and the controls, is modeled in real-time using the Real-Time Digital Simulator (RTDS) for power systems. The 200MW distributed PV modelling (area of 4.24 kilometres by 1.81 kilometres) is represented by four 50 MW PV plant equivalents in the RTDS simulation.

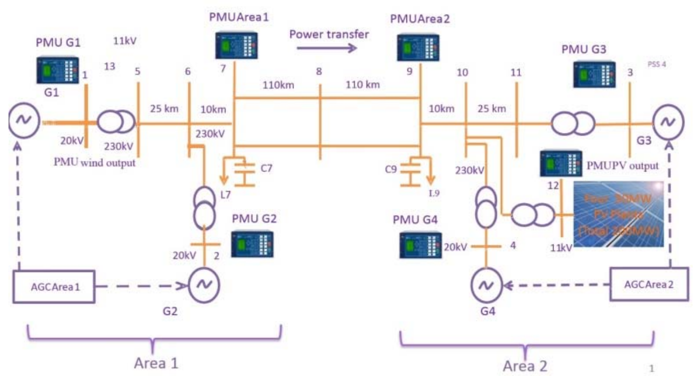

Figure 3 Two-area four machine power system with a 200MW PV plant connected at bus 12 in Area 2. Each power system area is equipped with an automatic generation controller. Automativ generation control (AGC) in Area 1 performs tie-line bias control and AGC in Area 2 performs frequency control

A real-time prediction is carried is carried out using ESN with multiple predicted PV power outputs as shown in Figure 4. The RTPIS Lab weather is used to study natural behavior of the 200 MW PV plant and the power system's reaction to the PV power fluctuations. A typical prediction result of the PV power 90s ahead is shown in Figure 5. More details on this study can be found in [17]. The next section describes how the predicted power is used in enhanced automatic generation control.

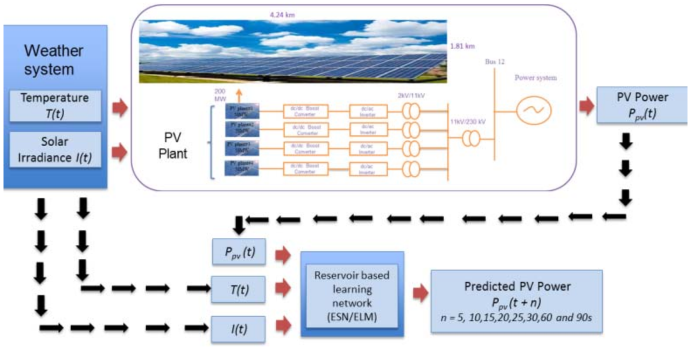

Figure 4 Schematic diagram of a real-time similation of a large PV plant consisting of four 50 MW PV plants with actual weather at the RTPIS Lab., Clemson, SC, USA

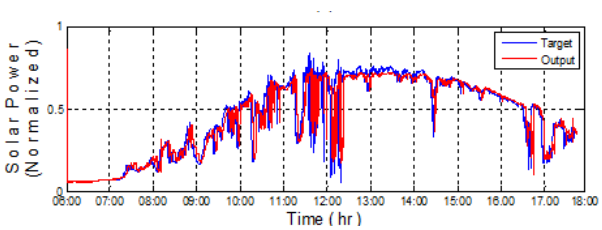

Figure 5 PV power prediction 90s ahead by an ESN

TIE-LINE BIAS CONTROL WITH LARGE PV POWER PLANTS

For bulk power systems with large PV plants, energy storage technologies are expensive. An integrated approach of hybrid technologies is the way forward to absorb high levels of renewables penetration. A supplementary or alternative approach to energy storage systems is to identify in multi-area interconnected power systems, potential areas for integration of large PV plants and other areas with excess generation and appropriate control technologies for balancing power and frequency fluctuations in the system as a result of large variable and uncertain PV penetration. The system in Figure 3 is one such system where Area 1 supplies the load in Area 2. Automatic generation control with tie-line power flow control was implemented in Area 1 to maintain the desired system frequency and to minimize power fluctuations [8].

In order to leverage interconnected systems to maximize high levels of PV penetration, accurate PV power predictions in short term into the AGC systems of supporting areas is necessary as shown in Figure 6. AGC is capable of increasing/decreasing power outputs of conventional generators (G1 and G2) in Area 1, varying the tie-line power flow to balance the PV power variability and achieve maximum penetration of PV power in Area 2. The optimal frequency bandwidth of the AGC is determined by simulating the system with different PV power prediction time steps. Phasor measurement units (PMUs) are used to provide input signals to the automatic generation controllers in the two area power system. Figure 7 shows the result of enhanced AGC on tie-line power flow during day time operation recorded on August 22th, 2014 with the ESN model based prediction. The predicted PV power is 35s ahead (optimal time step) in this case study. This study has demonstrated that it is possible to implement a dynamic tie-line bias control to sustain short-term high PV power variability. More details on this study can be found in [18].

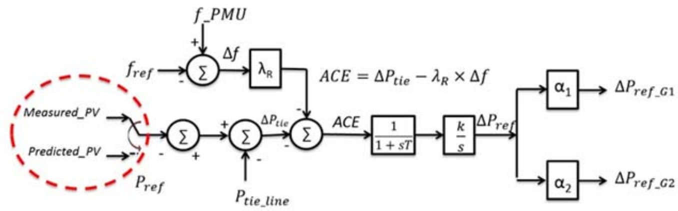

Figure 6 Block diagram of automatic generation controller in Area 1 of the power system in Figure 3 showing measured/predicted PV power utilized as control input

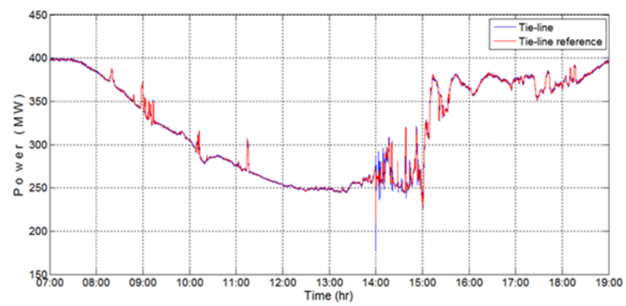

Figure 7 Tie-line power flow during day time operation recorded on August 22th, 2014 with the ESN model based prediction

OPTIMAL CONTROL OF PV SYSTEMS

Traditionally, PV energy dispatch controllers have been simple devices that do not assign priority to various loads. Instead, they attempt to power all loads all of the time, and if there is any excess energy, then that excess energy is used to charge the batteries. Researchers including those of RTPIS Lab have reported on improving the efficiency of photovoltaic systems by carrying out optimal control of PV systems [19-21].

The objective of the optimal energy dispatcher is on always meeting the critical load, followed by keeping the charge of the battery as high as possible so as to be able to power the critical load in cases of extended low output from the PV array, and lastly to power the non-critical load in so far as to not interfere with the first two objectives. Figure 8 and 9 shows a grid independent PV system and a schematic diagram of the simulated system on the RTDS in an energy management study at the RTPIS Lab, respectively [22]. An intelligent energy management demand response controller (IEMDC) is developed to meet the above mentioned objectives. Figures 10 and 11 show selective battery state of charge (SOC) operating performances of three controllers under different weather conditions. Herein, two types of fuzzy logic controllers have been developed to control the PV-battery system taking into some operating constraints in terms of power factors. One is an optimized fuzzy logic controller using mean-variance optimization [23] and the other is not.

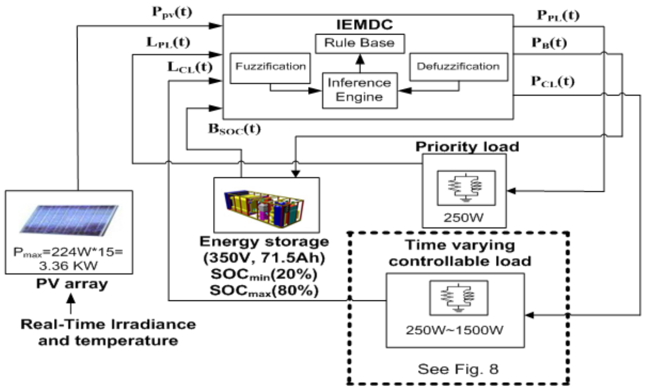

Figure 8 A PV-battery system with IEMDC [22]

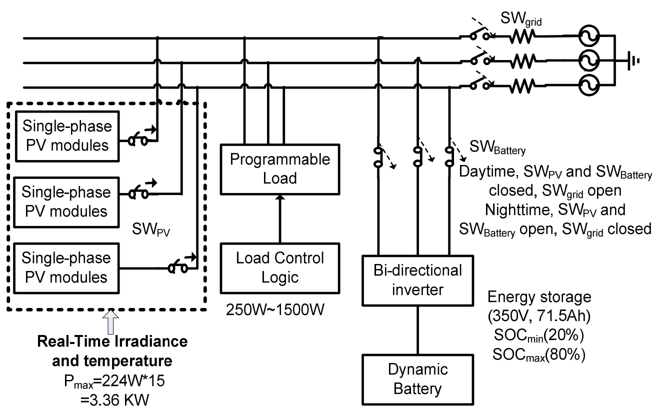

Figure 9 Schematic diagram of PV system simulated on the RTDS for energy management studies [22]

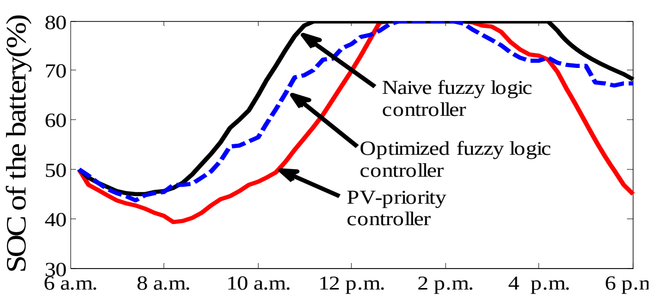

Figure 10 SOC of the battery on a moderate day [22]

Another optimal energy management controller approach is the adaptive critic designs (ACDs) [24]. A block diagram of the ACD approach is shown in Figure 12. An optimal energy dispatch controller was developed for a PV system similar to that in Figure 8 [21] and Figure 13 shows the battery state of charge for a PV system operating in Springfield, MO for the period of late fall and early winter using both a traditional PV-priority controller as well as the ACD based optimal PV controller developed using data from Caribou, Maine.

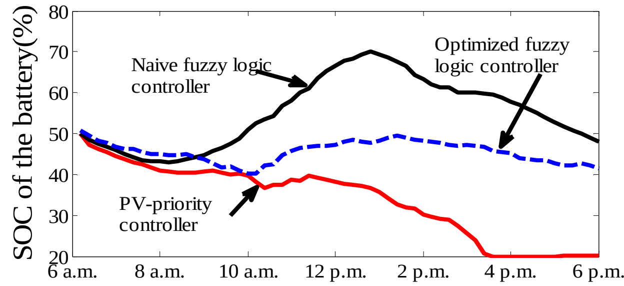

Figure 11 SOC of the battery on a cloudy day [22]

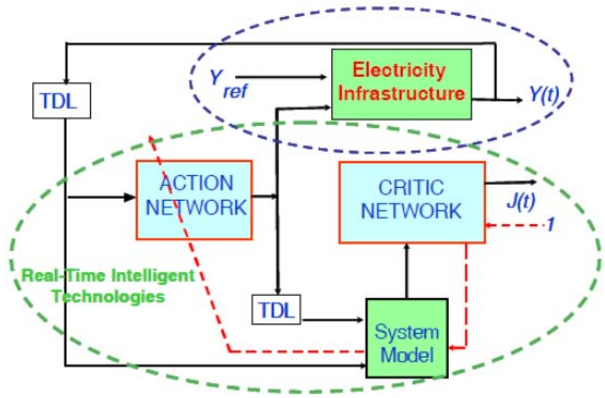

Figure 12 A block diagram of the ACD approach

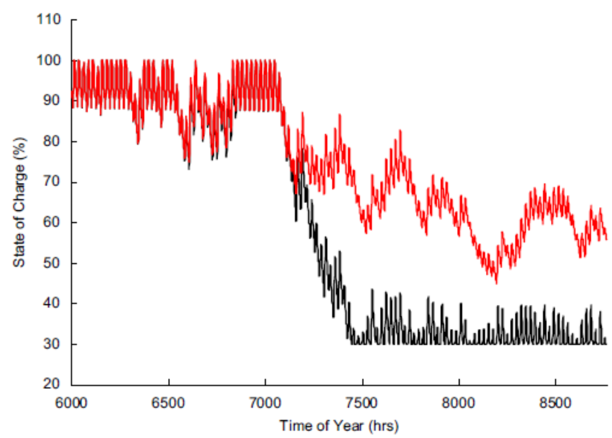

Figure 13 Battery SOC for a PV system operating in Springfield, MO for the period of late fall and early winter

As a result of optimal control systems, it is possible that a smaller (and cheaper) overall PV system utilizing optimal energy dispatch controllers would be suitable for meeting the same loads as a larger more expensive system not using an optimal controller. The maintenance and replacement cost of the battery is also reduced by approximately the same proportions as the life expectancy increase, since the battery will need to be replaced less often.

CONCLUSION

This paper has provided the potential of computational and optimization tools to address some of the grid operational concerns with high levels of PV penetrations. With modelling, predictions and optimal control of PV systems and its outputs, real time smooth operation of electric power systems with large PV power variability and uncertainty is possible.

ACKNOWLEDGEMENT

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