2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm), pp. 528-533, 5-8 November 2012

Solar Generation Prediction using the ARMA Model in a Laboratory-level Micro-grid

Rui Huang, Tiana Huang, Rajit Gadh
Smart Grid Energy Research Center, Mechanical Engineering, University of California, Los Angeles, USA
Na Li
Control and Dynamical Systems, California Institute of Technology, USA

***Abstract*—The goal of this article is to investigate and research solar generation forecasting in a laboratory-level micro-grid, using the UCLA Smart Grid Energy Research Center (SMERC) as the test platform. The article presents an overview of the existing solar forecasting models and provides an evaluation of various solar forecasting providers. The auto-regressive moving average (ARMA) model and the persistence model are used to predict the future solar generation within the vicinity of UCLA. In the forecasting procedures, the historical solar radiation data originates from SolarAnywhere. System Advisor Model (SAM) is applied to obtain the historical solar generation data, with inputting the data from SolarAnywhere. In order to validate the solar forecasting models, simulations in the System Identification Toolbox, Matlab platform are performed. The forecasting results with error analysis indicate that the ARMA model excels at short and medium term solar forecasting, whereas the persistence model performs well only under very short duration.**

I. Introduction

Current power grids are constantly facing reliable problems especially when unexpected periods of interruption occur. In recent years, the micro-grid has been proposed as a complimentary solution to help mitigate the reliability issues. The micro-grid, as part of the smart grid realization, consists of renewable generation, energy storage units and demand management through a low-voltage distribution network. Moreover, the micro-grid has the abilities to quickly respond to dynamic changes and island itself from the main grid [1]. Proliferation of renewable generation is one of the key drivers of establishing the need of micro-grid. Presently, renewable resources, e.g., solar energy, are employed globally due to the rapid development of the technologies and benefits to the environment. However, the integration of renewable generation into the micro-grid will require the assistant from forecasting. Forecasting is the ability to determine periods of stable generation from renewable sources. This is paramount to the reliability issues since it can reduce the uncertainty of the inconsistent renewable generation.

The objective of the article is to study solar generation forecasting in a laboratory-level micro-grid. The UCLA Smart Grid Energy Research Center (SMERC) performs research focusing on the integration of solar generation in a laboratory-level micro-grid [2], [3], [4]. Components of the laboratory-level micro-grid consist of solar PV panels, battery storage units and laboratory loads, such as laptops, LEDs and electric vehicles. The architecture of the laboratory-level micro-grid is displayed in Figure 1. Prediction models are developed to obtain accurate solar generation forecasting, which benefit the micro-grid by determining available power at any time and balancing the loads accordingly. The prediction models used in the article include the auto-regressive moving average (ARMA) model and the persistence model, due to their applicability in the micro-grid. The advantages for using the ARMA model and the persistence model are their simplicity, cost-effectiveness and accuracy for timely forecasting. The purpose of the research is not to compete with a variety of solar forecasting tools that are academically or commercially available today, but to generate our own solar forecasting results using the simple, inexpensive and effective methods, based on the environment of UCLA, which can be implemented for the laboratory-level micro-grid.

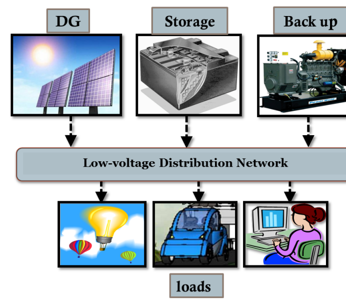

Figure 1. The laboratory-level micro-grid with solar PV panels, battery storage units and lab loads for the UCLA SMERC

Section II summarizes various existing forecasting methods. In addition, an investigation into the existing academic and commercial forecasting tools is provided. In Section III and IV, the ARMA and the persistence models are introduced, and the forecasting procedures for both models are described step-by-step respectively. The forecasting results with error analysis are presented in Section V. Conclusion of findings and future work are documented in Section VI.

II. Literature Review

A. Forecasting Methods

Both references [5] and [6] carry out surveys on the current status of the art in solar forecasting. Essentially, the existing solar forecasting methods can be categorized into persistence method, satellite data/imagery method, numeric weather prediction (NWP) method, statistical method and hybrid method. A general overview of the solar forecasting methods is presented in Table I.

Table I
SUMMARY OF THE FORECASTING METHODS

Method	*Description*	*Time Horizon*	*Example*
Persistence	High correlations between past and future	Very short term	CAISO
Satellite Data /Imagery	Data analysis and image processing	Short term	UCSD
NWP	Physical model	Long term	UCSD
Statistical	Mathematical model	Short and medium term	UCLA
Hybrid	Combination of different approaches	Adjustable	CAISO

The simplest way to perform a solar forecasting is to use persistence method. California Independent System Operator (CAISO) uses persistence method in its renewable energy forecasting and dispatching [7]. This method is highly effective in very short term prediction, i.e., 1 hour-ahead. It is often used as a comparison to other advanced methods. References [8] and [9] describe the method based on satellite data/imagery. Satellite data/imagery provides important atmospheric and meteorological information on cloudiness, cloud motion vector, etc., for predicting the solar irradiance. This method is evaluated to be the best method for 1 to 5 hour-ahead forecasting according to reference [5]. NWP method models solar radiation in the air with consideration of the cloud layers in the forecasting process. It is deemed to be the most successful method for long term solar forecasting, e.g., day-ahead, at present. Results from NWP method exhibit higher accuracy for longer time horizons as presented in references [10] and [11]. Statistical method develops mathematical models which include auto-regressive with exogenous input (ARX), ARMA, auto-regressive integrated moving average (ARIMA) and artificial neural network (ANN). This method is based on training the historical data spanning over a long time period, e.g., one year, to tune the model coefficients. References [10], [12] and [11] use ARX, ARIMA and ANN to predict the solar generation respectively. They perform well in the time horizons ranging from 1 hour up to 36 hours, which are short and medium term forecastings. In practice, as numerous articles concluded, hybrid method is a combination of different approaches that can be applied to obtain an optimal solar prediction. For example, references [5] and [6] both recommend a combination of NWP method and a statistical post-processing tool as a promising option for solar prediction.

B. Forecasting Tools

In this section, we explore the existing academic solar forecasting tools and commercial solar forecasting providers. Most of the forecasting tools and providers apply the satellite data/imagery and NWP methods. According to the investigation, Green Power Research offers solar forecasting service and solar resource assessment based on geostationary operational environmental satellite imagery, for utilities, independent system operators (ISO) and solar power producers[13]. 3Tier offers a solar predictor based on NWP method, with the integration of cloud forecasting capability [14]. AWS Truepower (AWST) offers a solar forecasting system based on NWP method, with statistical procedures for cloud pattern tracking [15]. SolarAnywhere offers solar forecasting up to 7 day-ahead based on satellite data such as cloud motion vector for short term forecasting, and NWP method for long term forecasting [16]. SolarCasters offers solar predictions for day-ahead and hour-ahead, and delivers both irradiance forecasting and plant-specific generation forecasting using TRNSYS simulation software based on NWP method, with proprietary radiative transfer models to predict the irradiance reaching the ground [17]. SOLARFOR offers solar power predictions for 0-48 hour-ahead based on NWP method [18]. Atmospheric and Environmental Research (AER) Solar Forecast offers solar forecasting based on satellite data observations and NWP method, as well as with proprietary radiative transfer models [19]. Solar2000 offers solar irradiance forecasting at 1 to 1, 000,000 nm throughout the solar system based on NWP method, with measuring sun rotation and infrared wavelength [20].

III. FORECASTING SETUP FOR THE ARMA MODEL

The ARMA model, also known as the Box–Jenkins model (1976), is one type of the time-series models in statistical method. It can be used to solve the problems in the fields of mathematics, finance and engineering industry that deal with a large amount of observed data from the past. The model description and forecasting procedure for the ARMA model are explained as below.

A. Model Description

The ARMA model is developed using Equation 1. It consists of two parts, the auto-regressive (AR) part and the moving average (MA) part.

$$S(t) = \sum_{i=1}^{p} \alpha_i S(t-i) + \sum_{j=1}^{q} \beta_j e(t-j) \tag{1}$$

In Equation 1, $S(t)$ is the forecasted solar generation at time t. In the AR part, p is the order of the AR process, and α_i is the AR coefficient. In the MA part, q is the order of the MA error term, β_j is the MA coefficient and $e(t)$ is the white noise that produces random uncorrelated variables with zero mean and constant variance [21]. Typically, this method requires a large amount of historical data, e.g., one year, to obtain the ARMA model. That is to find the orders p, q and the coefficients α_i, β_j. In addition, due to the geographical differences, each location corresponds to its own unique model. Based on the given historical data, the construction of the model for each location consists of two phases, identifying the orders p, q and determining the coefficients α_i, β_j. In particular, we limit $p, q \leq 10$ to simplify the process. The algorithms to realize the model are discussed in Step III-B3.

B. Forecasting Procedure

The five steps below are followed to complete the forecasting process.

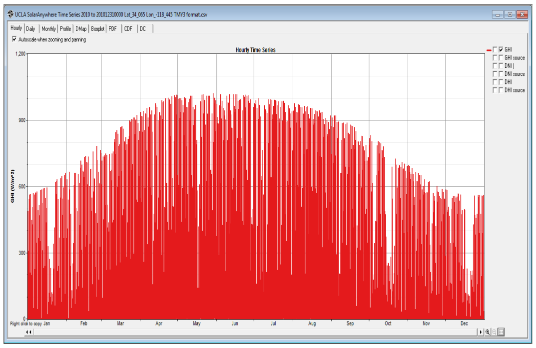

Figure 2. Hourly GHI in 2010 for the UCLA SMERC

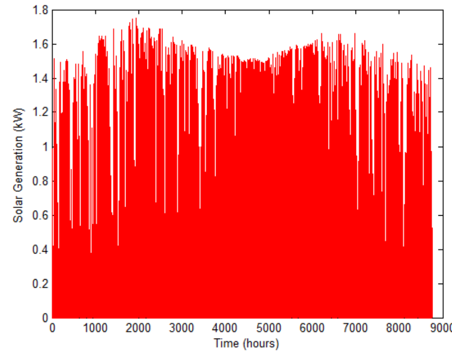

Figure 3. Hourly solar generation simulated by SAM with 1 kW PV in 2010 for the UCLA SMERC

1) Obtain the historical solar radiation data: Since we aim to forecast the solar generation for the laboratory-level micro-grid, the traces of historical solar generation data are used as the input of the ARMA model. In the first step, we collect hourly solar radiation data from SolarAnywhere, a web-based service that offers hourly global horizontal irradiance (GHI), direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) for locations within the U.S.A. that dates from 1998 to 2011 [16]. The data we collect covers the entire year from Jan. 1st, 2010 to Dec. 31st, 2010 for the vicinity of UCLA, California (latitude 34.065, longitude -118.445). The Figure 2 shows the hourly GHI in 2010 for the UCLA SMERC, which is the most essential solar radiation data for generating solar energy.

2) Simulate the historical solar generation data: We use System Advisor Model (SAM) to produce the hourly solar generation data from Jan. 1st, 2010 to Dec. 31st, 2010, with inputting the hourly solar radiation data from SolarAnywhere. As a performance-based model in the renewable energy industry, SAM can promptly assist the decision making process in various aspects of solar power generation [22]. To be more specific, it has functions of modeling PV system and simulating the solar production. Our design of the PV system in SAM is composed of a desired array (size of 1 kW dc), a module (SAM/Sandia Modules/SunPower SPR-210-BLK [2007(E)]) and a grid-connected PV inverter (capacity of 4 kW ac). The solar generation data simulated by SAM is shown in Figure 3. It is estimated that the total solar generation in 2010 for the UCLA SMERC is 3.324 MW and the peak is 1.7491 kW with the average of 0.3795 kW.

3) Realize the ARMA model: The mathematical methods of finding the orders and coefficients of the ARMA model are introduced in reference [23]. The order identification is proposed by Daniel and Chen (1991), and coefficients determination is calculated by applying the Yule-Walker relations for α_i and the Newton-Raphson algorithms for β_j. In the article, the two-phase realization of the ARMA model is implemented in the System Identification Toolbox, Matlab platform [24]. By inputting the data resulted from SAM into Matlab, the System Identification Toolbox is capable of constructing mathematical models, i.e. finding the orders and coefficients in Equation 1. As a result, the realized ARMA model is able to deliver time-series output for forecasting in the next step.

4) Predict the future values: The future values can be predicted using the realized ARMA model. For example, Equation 2 is applied to predict the h hour-ahead forecasting ($h = 1, 2, 3$...hours).

$$S(t+h) = \sum_{i=1}^{p} \alpha_i S(t-i) + \sum_{j=1}^{q} \beta_j e(t-j) \tag{2}$$

where $S(t+h)$ is the forecasted solar generation at time $t+h$.

5) Analyze the errors: In order to measure the accuracy of the predictions, the errors between the forecasted values and actual data are analyzed here. In the forecasting procedure, we train the hourly solar generation data for 2010 to obtain the ARMA model, and use the model to forecast the hourly solar generation values for 2011, for the UCLA SMERC. In the article, Mean Absolute Error (MAE) and Mean Squared Error (MSE), defined in Equation 3 and 4, are used as the errors to validate the prediction method.

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |A(t) - F(t)| \tag{3}$$

$$MSE = \frac{1}{n} \sqrt{\sum_{t=1}^{n} (A(t) - F(t))^2} \tag{4}$$

where n is the length of the time horizon, i.e., $n = 744$ if we choose January for the time horizon, and $A(t)$ and $F(t)$ denote the actual data and the forecasted value at time t. In the forecasting procedure, the historical data are for 2010 from Step III-B2, the forecasted values are for 2011 from Step III-B4 and the actual data are for 2011 from SAM. The data entered into SAM are the solar radiation data for 2011 from SolarAnywhere.

IV. Forecasting Setup for the Persistence Model

A. Persistence Model

As a comparative study, the persistence model is developed using Equation 5 to predict the h hour-ahead forecasting ($h =$

1, 2, 3...hours).

$$S(t+h) = S(t) \tag{5}$$

where $S(t+h)$ is the forecasted solar generation at time $t+h$.

B. Forecasting Procedure

Similarly, the forecasting procedure for the persistence model includes obtaining the historical solar radiation data from SolarAnywhere, simulating the historical solar generation data by SAM, predicting the future values by applying Equation 5 and analyzing the errors. Differently, the historical data and the actual data are the same, both for 2011 from SAM. The data entered into SAM are the solar radiation data for 2011 from SolarAnywhere.

V. Forecasting Results

A. The realized ARMA model

We conduct the Matlab simulations to obtain the ARMA model. Table II presents the values of the orders and coefficients for the ARMA model for the UCLA SMERC.

Table II
THE REALIZED ARMA MODEL

p	q	α_i	β_j
2	3	$\alpha_1 = -1.597$ $\alpha_2 = 0.6882$	$\beta_1 = -0.2072$ $\beta_2 = 0.1768$ $\beta_3 = 0.0513$

B. The forecasted values and actual data

Figure 4 shows the curves of the forecasted solar generation and actual data for 1 hour-ahead on Jan. 1st, 2011 for the laboratory-level micro-grid. Figure 5 shows the curves of the forecasted solar generation and actual data for 1 hour-ahead on Jul. 1st, 2011. There are at least three points that are of interest.

- On Jan. 1st, for the very short term forecasting, i.e., 1 hour-ahead, the curve produced by the ARMA model resembles the actual data from 6:00 AM to 11:00 AM but varies considerably at a later time. In particular, there is a small fluctuation around 4:00 AM. However, such time periods cannot obtain much sunlight. Therefore, there is a need to improve the model by taking actual weather data into account in the future.
- On the other hand, the curve produced by the persistence model has a tiny shift along the time horizon compared to the actual data. Nonetheless, this model is still accurate.
- On Jul. 1st, the ARMA model matches more closely to the actual data than that on Jan. 1st. The ARMA model performs better in the prediction during the months that have more sunlight. Similar errors are found around 4:00 AM, which emphasize the importance of improving the ARMA model by considering actual weather data. Similarly, the persistence model performs well in the 1 hour-ahead forecasting on Jul. 1st.

Figure 6 and Figure 7 show the curves of the forecasted solar generation and actual data for 3 hour-ahead on Jan. 1st and Jul. 1st, 2011 for the laboratory-level micro-grid respectively. There are at least three points that are of interest.

- Both on these two days, the ARMA model presents better predictions than the persistence model for short term forecasting, i.e., 3 hour-ahead, which illustrates that the persistence model is only accurate for very short term forecasting.
- For the predictions based on the ARMA model, it is evident that the results for 1 hour-ahead are better than 3 hour-ahead. The prediction accuracy decreases as the hour-ahead increases.
- Similar trends can be found for the persistence model. The prediction accuracy decreases considerably as the hour-ahead increases.

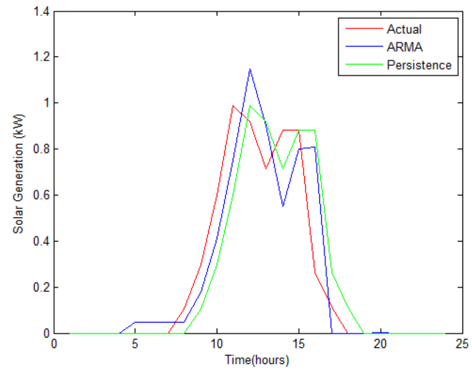

Figure 4. 1 hour-ahead solar generation forecasting and actual data on Jan. 1st, 2011 for the UCLA SMERC

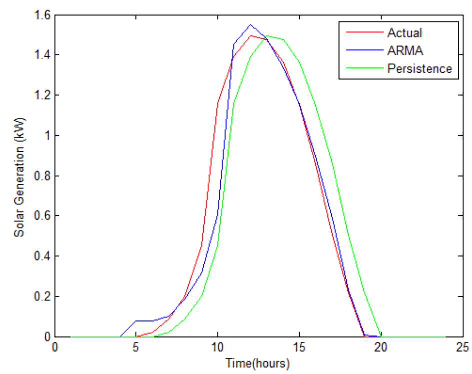

Figure 5. 1 hour-ahead solar generation forecasting and actual data on Jul. 1st, 2011 for the UCLA SMERC

C. The Error Analysis

As mentioned in Step III-B5, we use MAE and MSE to measure the accuracy. Figure 8 shows the distributions of the MAE for each month during 2011 for 1 hour-ahead forecasting, for the ARMA model and the persistence model respectively. There are at least three points that are of interest.

- For each month of the year, the MAE of the ARMA model is smaller than the persistence model, which translates into the conclusion that the ARMA model is

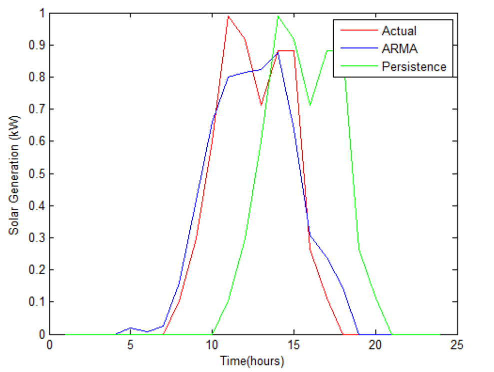

Figure 6. 3 hour-ahead solar generation forecasting and actual data on Jan. 1st, 2011 for the UCLA SMERC

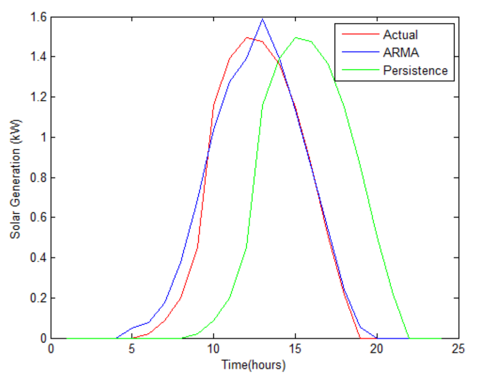

Figure 7. 3 hour-ahead solar generation forecasting and actual data on Jul. 1st, 2011 for the UCLA SMERC

more reliable for 1 hour-ahead forecasting. Take January as example, the ARMA model shows an improvement of as much as 17.62% compared to the persistence model.

- The maximum MAE of the ARMA model is 0.1013 kW in March while the minimum MAE is 0.073 kW in July, with the average MAE of 0.0894 kW.
- The maximum MAE of the persistence method is 0.1322 kW in April while the minimum MAE is 0.1033 kW in January, with the average MAE of 0.1213 kW.

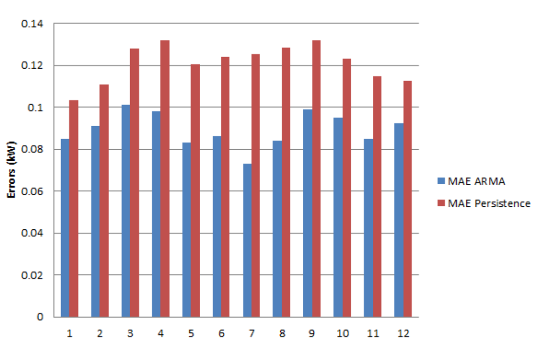

Figure 8. The MAE of the ARMA model and the persistence model for 1 hour-ahead forecasting for each month of 2011 for the UCLA SMERC

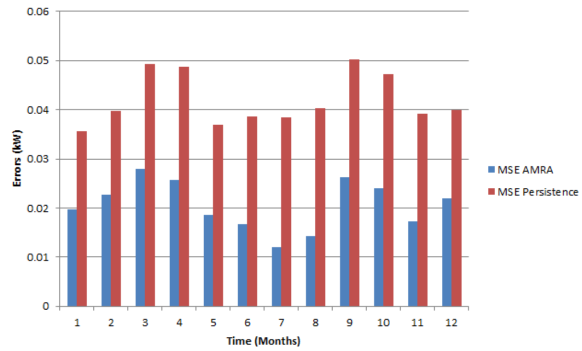

Figure 9. The MSE of the ARMA model and the persistence model for 1 hour-ahead forecasting for each month of 2011 for the UCLA SMERC

Figure 9 shows the distributions of the MSE for each month during 2011 for 1 hour-ahead forecasting, for the ARMA model and the persistence model respectively. There are at least three points that are of interest.

- Similar trends can be found in this comparison. The MSE of the ARMA model is smaller than the persistence model, for each month of the year for 1 hour-ahead forecasting. Take January as example, the ARMA model shows an improvement of as much as 44.38% compared to the persistence model.
- The maximum MSE of the ARMA model is 0.028 kW in March while the minimum MAE is 0.0121 kW in July, with the average MAE of 0.0206 kW.
- The maximum MAE of the persistence model is 0.0502 kW in September while the minimum MAE is 0.0356 kW in January, with the average MAE of 0.042 kW.

Figure 10 shows the variations of the MAE and the MSE for different hour-ahead forecasting, in July, 2011. The hour-ahead ranges from 1 to 5. There are at least three points that are of interest.

- As results illustrated, as the forecasting hour-ahead increases, the MAE and the MSE for each model increase accordingly. However, they increase by different degrees for different models. Generally speaking, the errors of the ARMA model are smaller than the persistence model.
- The errors in the ARMA model varies steadily. When the hour-ahead is larger than 4, the MAE and the MSE almost remain constant. The results further demonstrate that the ARMA model is suitable for short and medium term forecasting.
- The errors in the persistence model increase considerably as the hour-ahead increases. The results further demonstrate that the persistence model is only suitable for very short term forecasting.

VI. Conclusions

Solar generation can be gradually integrated into the power grid starting at the micro-grid level, as the prominent power generation technology for the UCLA SMERC. Due to the unpredictability and variability of the current solar generation,

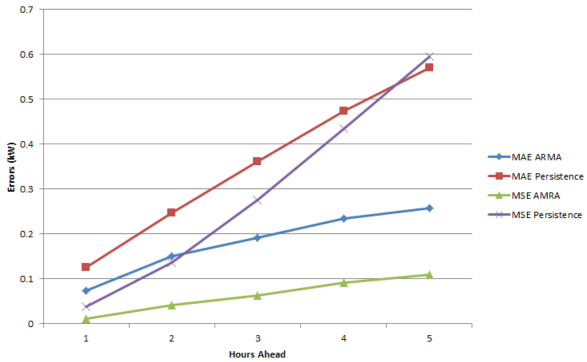

Figure 10. The MAE and MSE of the ARMA model and the persistence model in July, 2011 for different hour-ahead forecasting for the UCLA SMERC

the wide adoption of solar generation forecasting is still underway.

According to the reviews carried out in the article, based on the assessment of solar forecasting methods, statistical method performs well for solar generation prediction especially for short and medium term. Currently, academic and commercial forecasting models have their unique identities, and perform well depending on whether it is for short term or long term forecasting. We suggest that a combination of solar forecasting models should be used to solve the reliability issues associated with the integration of solar generation into the micro-grid.

As discussed in the article, statistical method typically uses time-series models such as the ARMA model to obtain desirable forecasting results. We extract information from current forecasting algorithms and produce our own forecasting procedure for the ARMA model. The procedure includes obtaining the historical solar radiation data from SolarAnywhere, simulating the historical solar generation data by SAM, realizing the ARMA model, predicting the future values and analyzing the errors. In the meanwhile, we use the persistence model as a comparison. The error analysis reveals that the ARMA model is preferred for short and medium term prediction on a micro-grid level. Moreover, results indicate that the persistence model performs well in very short term prediction.

The next step is to produce a hybrid energy system that includes solar PV panels and battery storage units, in order to realize the isolated operation for some periods of time. Continuous research is needed to establish hybrid method to improve the prediction of its solar generation output.

ACKNOWLEDGEMENT

This work is supported by Smart Grid Energy Research Center (SMERC), UCLA, U.S.A. and Korean Institute of Energy Research (KIER), Korea.

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